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AGENT-BASED SIMULATION OF ELECTRIC VEHICLES: DESIGN AND IMPLEMENTATION OF A FRAMEWORK

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Abstract

Major global concerns for today's world are the implications of climate change and future energy security. The transportation sector plays an important role within this context, as it currently heavily relies on fossil fuels. In order to break this dependence, electric vehicles could play a key role, especially due to their greater energy conversion efficiency compared with conventional vehicles. Furthermore, by using electricity these vehicles can play an important role in the energy system of the future, where energy generation is envisioned to be more sustainable, incorporating a higher share of renewable energy resources. However, as many of these energy sources are intermittent and require energy storage capacities, the batteries of electric vehicles could take up this role; by exchanging information between electricity demand and supply stakeholders in real-time ("smart grid"), an electric vehicle would charge at times of electricity oversupply and stop charging or even supply energy back to the grid for short periods in times of electricity generation shortage, in order to stabilize the electricity network ("vehicle to grid").

But there are also concerns that the electricity grid, which has not been designed with dynamic demands in time and space in mind, could suffer from the large scale integration of electric vehicles. This could manifest itself in powerline and transformer overloads on lower levels of the electricity network distribution infrastructure. This security and stability of the gird is further at risk due to increased distributed energy generation (including alternative energy) and the liberalization of electricity markets. In this case electricity is traded beyond national borders, leading to possible congestion at powerlines. In order to support the analysis and future design of such complex systems including electric vehicles, integrated modeling of energy demand and supply is needed. This dissertation proposes a framework for such modeling, with particular focus on electricity demand modeling for electric vehicles.

As many problems within this context require disaggregated models in time and space, e.g. to uncover bottlenecks in the electricity grid, an existing agent-based travel demand simulation called MATSim is used, which allows the modeling of individual preferences. In order to prepare MATSim for simulation of large scale disaggregated electric vehicle scenarios, a new traffic micro-simulation model is implemented together with other performance enhancements to the framework, making use of parallel computation. Additionally, the current parking model in MATSim is re-

placed by a new parking model, which takes parking supply constraints into account and also supports special parking for electric vehicles with integrated electricity charging facilities. The parking choice model has been developed further towards an initial parking search model in the course of this dissertation.

Based on this work, a framework has been developed that integrates various models, including a vehicle fleet definition, vehicle energy consumption models and electricity charging models. In addition, various types of charging infrastructure are modeled including stationary infrastructure with plugs and inductive charging along roads. Furthermore, several types of charging schemes are available including *smart charging*, where an intelligent central entity in the smart grid is assumed which controls the charging of vehicles.

During the course of this dissertation it became evident that there is a lack of integrated and detailed electricity demand and supply models, which hampers interdisciplinary work in the field. Therefore, the framework is being generalized and published as open source under the name "Transportation Energy Simulation Framework". For many models only basic implementations and interfaces are provided. The idea is that other researchers who are experts within their fields can build on top of it, for example models for "vehicle to grid" applications.

A case study for the city of Zurich is presented in this dissertation, which highlights the capabilities of the framework to uncover possible bottlenecks in the electricity network. Furthermore, the case study also highlights the ability of the models to support policy design. To the best of the author's knowledge such integrated modeling is the first of its kind, in terms of methodology, spatial and temporal resolution and scenario size.

Kurzfassung

Heutzutage stehen Fragen bezüglich möglicher Folgen des Klimawandels und Energiesicherheit im globalen Fokus. In diesem Umfeld spielt der Transportsektor eine wichtige Rolle, da dieser derzeit hauptsächlich auf fossile Energieträger angewiesen ist. Um diese Abhängigkeit zu reduzieren, könnten elektrische Fahrzeuge eine zentrale Rolle einnehmen, insbesondere wegen ihrer höheren Engerieumwandlungseffizienz im Vergleich zu herkömmlichen Fahrzeugen. Da diese Fahrzeuge mittels Elektrizität betrieben werden, könnten sie eine wichtige Rolle im Energiesystem der Zukunft einnehmen, in welchen die Energiegewinnung zunehmend nachhaltiger gestaltet werden soll und der Anteil der erneuerbaren Energiequellen zunehmen soll. Da aber die Gewinnung erneuerbarer Energie zeitlich fluktuieren kann und unzuverlässig ist, braucht es Energiespeicherkapazitäten. Die Batterien der elektrischen Fahrzeuge könnten diese Rolle übernehmen, indem sie in Echtzeit Information zwischen Energienachfrage und Energieanbieter austauschen könnten. Dadurch könnten die Batterien zu jenen Zeiten aufgeladen werden, wo es ein Energieüberangebot gibt, und aufhören zu laden oder sogar Energie ins Netz für kurze Zeiten entladen, wenn es Engpässe in der Energiegenerierung gibt, um das elektrische Netz zu stabilisieren.

Es bestehen aber Bedenken, dass das elektrische Netz, welches nicht für eine solche dynamische Nachfrage konzipiert wurde, durch eine grossflächige Integration elektrischer Fahrzeuge in Mitleidenschaft gezogen werden könnte. Dies könnte sich in Form von Stromleitungs- und Transformatorenüberladungen ausdrücken, insbesondere auf tieferen Ebenen des elektrischen Netzes. Die Sicherheit und Stabilität des elektrischen Netzes sind des Weiteren durch die verteilte Energieerzeugung und die Liberalisierung der Strommärkte gefährdet. In letzteren Fall wird der elektrische Strom über Landesgrenzen hinaus gehandelt, welches zu Engpässen in Stromübertragungsleitungen führen kann. Um die Analyse und das zukünftige Design eines solch komplexen Systems mitsamt elektrischen Fahrzeugen zu untersuchen, ist eine integrierte Modellierung von elektrischer Nachfrage und Angebot erforderlich. Diese Dissertation schlägt für solche Modellierung ein Framework vor, welches insbesondere auf die Modellierung elektrischer Nachfrage durch elektrische Fahrzeuge fokussiert.

Aufgrund der erforderlichen Detailliertheit in Raum und Zeit bedarf es disaggregierter Modelle, z.B. um Engpässe im elektrischen Netz aufzudecken. Deshalb wird die agenten-basierte Nachfragesimulation MATSim verwendet, welche es erlaubt individuelle Präferenzen von Personen zu modellieren. Um MATSim für die Simulation grosser und disaggregierter Szenarien vorzubereiten, wurde ein neues Verkehrs-Mikrosimulationsmodell implementiert und weitere Laufzeitverbesserungen des Frameworks vorgenommen, wobei insbesondere Parallelkalkulationen zum Einsatz kamen. Zusätzlich wurde das aktuelle Parkmodell in MATSim durch ein neues Parkmodell ersetzt, welches Parkangebotsbeschränkungen berücksichtigt und auch spezielle Parkplätze für Elektrische Fahrzeuge mit Lademöglichkeiten integriert. Auch wurde dieses Modell hingehend zu einem initialen Parksuchmodel erweitert.

Basierend auf diesen Arbeiten wurde ein Framework entwickelt, welches die diversen Modelle integriert, inklusive eines Fahrzeugflottenmodells, Fahrzeugenergieverbrauchsmodells und diverser Elektrizitätsauflademodelle. Zusätzlich wurden diverse Typen von Auflade Infrastrukturen modelliert, inklusive stationärer Auflade Infrastruktur mit Stromstecken und induktives Aufladen entlang von Strassenzügen. Des Weiteren sind diverse Typen von Aufladearten verfügbar, inklusive „Intelligentes Aufladen“, bei welchen eine zentrale Einheit im Stromnetz angenommen wird, welche das Aufladen der Fahrzeuge steuert.

Während dem Werdegang dieser Dissertation wurde klar, dass es einen Mangel an integrierten Modellen für detaillierte Elektritzitätsnachfrage- und Angebotsmodellierung gibt, welche die interdisziplinäre Arbeit in diesem Fachgebiet beeinträchtigt. Deshalb wird das Framework verallgemeinert und Opensource unter dem Namen “Transportation Energy Simulation Framework” zur Verfügung gestellt. Für viele mögliche Anwendungen stehen Grund Implementationen samt Schnittstellen zur Verfügung. Die Idee ist, dass andere Forschende, welche Experten in ihren jeweiligen Gebieten sind, darauf aufbauen und das Framework erweitern können.

Es wird eine Fallstudie für Zürich in der Dissertation präsentiert, wo das Framework benutzt wird um mögliche Engpässe im elektrischen Netz aufzudecken. Auch zeigt die Fallstudie Möglichkeiten auf um Entscheidungsprozesse zu unterstützen. Gemäss dem Wissen des Autors ist die integrierte Modellierung die erste ihrer Art, aufgrund der Methodik, geographischer und zeitlicher Auflösung sowie Grösse der möglichen Szenarien.

List of Publications

In the following a list of publications is provided, which were authored/co-authored during the course of this dissertation.

Refereed Journal Papers

Galus, M.D., **R.A. Waraich**, F. Noembrini, K. Steurs, G. Georges, K. Boulouchos, K.W. Axhausen and G. Andersson (2012) Integrating power systems, transport systems and vehicle technology for electric mobility impact analysis and efficient control, *IEEE Transactions on Smart Grid*, **3** (2) 934-949.

Horni, A., L. Montini, **R.A. Waraich** and K.W. Axhausen (2013) An agent-based cellular automaton cruising-for-parking Simulation, Transportation Letters, **5** (4) 167-175.

Saner, D., N. Heeren, B. Jäggi, **R.A. Waraich** and S. Hellweg (2013) Housing and mobility demands of individual households and their life cycle assessment, *Environmental Science & Technology*, **47** (11) 5988-5997.

Waraich, R.A. and K.W. Axhausen (2012) Agent-based parking choice model, *Transportation Research Record*, **2319**, 39-46.

Waraich, R.A., M.D. Galus, C. Dobler, M. Balmer, G. Andersson and K.W. Axhausen (2013) Plug-in hybrid electric vehicles and smart grid: investigations based on a micro-simulation, *Transportation Research Part C*, **28**, 74-86.

Waraich, R.A., C. Weis, C. Dobler and K.W. Axhausen (submitted for publication) Optimizing parking prices using an agent based approach, paper submitted to *Transport Policy*.

Zheng, N., **R.A. Waraich**, K.W. Axhausen and N. Geroliminis (2012) A dynamic cordon pricing scheme combining the macroscopic fundamental diagram and an agent-based traffic model, *Transportation Research A*, **46** (8) 1291-1303.

Refereed Papers in Proceedings and Books

Waraich, R.A., D. Charypar, M. Balmer and K.W. Axhausen (accepted for publication) Performance improvements for large-scale traffic simulation in MATSim, in M. Helbich, J.J. Arsanjani and M. Leitner (eds.) *Computational Approaches for Urban Environments*, Springer.

Waraich, R.A., G. Georges, M.D. Galus and K.W. Axhausen (2014) Adding electric vehicle modeling capability to an agent-based transport simulation, in D. Janssens, A. Yasar and L. Knapen (eds.) *Data Science and Simulation in Transportation Research*, 282-318, IGI Global, Hershey.

Conference Papers

Abedin, Z.U. and **R.A. Waraich** (2013) Modelling inductive charging of battery electric vehicles using an agent-based approach, paper presented at the *8th Conference on Sustainable Development of Energy, Water and Environment Systems,* Dubrovnik, Croatia, September 2013.

Galus, M. D., **R.A. Waraich** and G. Andersson (2011) Predictive, distributed, hierarchical charging control of PHEVs in the distribution system of a large urban area incorporating a multi agent transportation simulation, in *Proceedings of the Power Systems Computations Conference (PSCC)*, Stockholm, Sweden, August 2011.

Galus, M. D., **R.A. Waraich**, M. Balmer, G. Andersson and K. W. Axhausen (2009) A framework for investigating the impact of PHEVs. In *Proceedings* of the International Advanced Mobility Forum (IAMF), Geneva, Switzerland, March 2009.

González Vayá, M., M.D. Galus, **R.A. Waraich** and G. Andersson (2012) On the interdependence of intelligent charging approaches for plug-in electric vehicles in transmission and distribution networks, *Proceedings of the IEEE ISGT Europe Conference*, Berlin, October 2012.

González Vayá, M., T. Krause, **R.A. Waraich** and G. Andersson (2011) Locational marginal pricing based impact assessment of plug-in hybrid electric vehicles on transmission networks, presented at the *Cigré 2011 Bologna Symposium*, Bologna, September 2011.

Meister, K., M. Balmer, F. Ciari, A. Horni, M. Rieser, **R.A. Waraich** and K.W. Axhausen (2010) Large-scale agent-based travel demand optimization applied to Switzerland, including mode choice, paper presented at the *12th World Conference on Transportation Research*, Lisbon, July 2010.

Waraich, R.A., C. Dobler and K.W. Axhausen (2012) Modelling parking search behaviour with an agent-based approach, *13th International Conference on Travel Research Behaviour (IATBR)*, Toronto, July 2012.

Zheng, N., **R.A. Waraich**, N. Geroliminis and K.W. Axhausen (2011) Investigation of macroscopic fundamental diagrams in urban road networks using an agent-based simulation model, paper presented at the *11th Swiss Transport Research Conference*, Ascona, May 2011.

Other Publications

M. D. Galus, G. Georges, **R. A. Waraich** (2012) Final Project Report: Abating Road Emissions Through Efficient Electric Mobility Interactions with the Electric System (ARTEMIS), (in German), ETH Zürich, Switzerland, 2012.

Balmer, M., K. Meister, **R.A. Waraich**, A. Horni, F. Ciari und K.W. Axhausen (2010) Agentenbasierte Simulation für location based services, *Endbericht*, F&E Förderung: Science to Market, KTI **8443.1** ESPP-ES, Datapuls AG, IVT, ETH Zürich, Zürich.

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Chapter 1

Introduction

1.1 Background and Motivation

The discovery of new energy resources and new technologies to convert energy has resulted in increased comfort throughout human history. This is as true for cave dwellers' heating themselves at a campfire, as for today's people using various transportation modes, electrical appliances, heating, etc.

While we enjoy ourselves using these technologies, there are currently many issues and questions open with regards to energy. This includes concerns about climate change, peak-oil and energy security.

Solutions to this complex set of problems will require serious efforts from all stakeholders including individuals, politicians, science and industry. While individuals will need to adapt their behaviors to save energy, politicians will need to shape policies and incentives capable of driving such a development. Clearly science and industry both play an important role in advancing the research and development of more efficient appliances and ways to generate energy sustainably.

When analyzing the different problems related to energy, one finds that they are all strongly connected to the transportation sector. Therefore, in order to solve the overall energy problem, progress within the transportation sector is vital. There is a general consensus today that electric vehicles and plug-in-hybrid electric vehicles (which can be charged using a plug and also driven using gasoline), can play an important role towards a sustainable future (MacKay, 2009). In addition to their more efficient energy conversion compared with conventional vehicles and their zero emissions, such vehicles could also play a key role within the future energy system.

The future energy system will need to have a low carbon emission footprint in order to address concerns about climate change. While nuclear power meets this criteria, after the Fukushima nuclear disaster in March 2011, several countries especially in Europe have adapted policies against the use of nuclear energy (Wettneben, 2012). Two sustainable alternative ways of generating electricity are solar and wind power; however, unfortunately both of them are intermittent energy sources. This means that neither of them is continuously available and both have a variable supply, leading to occasional over and under supply of power. In order to solve this situation, the batteries of electric vehicles could play the role of electric storage units, which can be charged at times of oversupply and stop charging in times of electricity generation shortage. Furthermore, these batteries can even supply electricity back to the grid (called “vehicle-to-grid”).

While there are also additional potential uses of electric vehicles in the energy system of the future, there are also concerns about possible power-line and transformer overloads within the existing electricity networks (Farmer et al., 2010). Within this context, electric vehicle charging could be coordinated through the use of information and communication technologies, sometimes referred to as a “smart grid” (National Energy Technology Laboratory, 2007).

As analyzing such systems requires models with a high temporal and spatial resolution, the development of such models was proposed within the context of this dissertation. As a result a framework has been built for electric vehicle modeling, which allows the identification of possible bottlenecks in electricity networks and helps to perform integrated modeling of “smart grids”, distributed energy generation and many other current and possible future technologies. The framework expands on a framework for modeling travel demand (MATSim, 2013). While the focus of the dissertation is on electric vehicle demand modeling, the framework has been coupled with electricity network and electricity supply models which have been created in a parallel PhD dissertation (Galus, 2012). In order to demonstrate the power of such integration, the integrated energy demand and supply models have been applied to a large metropolitan area within a real world scenario to help the local utility company in their planning of the future electric grid.

1.2 Structure of the Thesis

In order to prepare the MATSim travel demand simulation tool for large scale simulation of electric vehicle scenarios, several models were developed and integrated in MATSim in parallel with the development of electric vehicle functionalities. This included a new traffic simulation model and a parking model. The need for the new traffic simulation model is motivated especially by the high computational requirements of high resolution large scale scenarios. This also includes additional performance related improvements and enhancements of the MATSim simulation.

Another enhancement of MATSim relates to the parking model in MATSim. This is essential for simulation of electric vehicle scenarios as the charging infrastructure of electric vehicles can also be located at parking spaces. Furthermore, by introducing parking supply constraints the attractiveness of an area for car use can be modeled more realistically.

The developments of the various models during the course of this dissertation has resulted in several papers and book chapters, most of which are included in this dissertation as separate chapters. In the following an overview of the chapters is given.

Chapter 2: This chapter presents the integration of a new traffic simulation model into MATSim, which increases the realism of the model and also drastically reduces the computational time. In this chapter the performance of the part of MATSim that processes the traffic simulation out is also improved. The performance of that part of MATSim is especially important as many electric vehicle related models depend on it.

Chapter 3: This chapter presents the successful integration of electric vehicle demand models and models of electricity network flow and supply. The chapter includes experiments related to various charging schemes and identification of bottlenecks in the grid. A smart grid application is also included, which avoids bottlenecks in the electricity network by centrally coordinating electric vehicle charging.

Chapter 4: This chapter presents a first parking model for MATSim, which takes parking supply, walking distance and parking fees into account. The model is applied to the city of Zurich. The same model is also used in Chapter 6 for simulation of the electric vehicle scenario in the city of Zurich.

Chapter 5: This chapter demonstrates how people's individual preferences collected using a stated preference survey, can be used in an extended version of the parking model presented in Chapter 4. The model is used to mimic performance based parking fees, which have been implemented in San Francisco since 2010 (SFpark, 2012). Similar pricing ideas can also be designed in the context of electric vehicles, therefore the experiments conducted provide new insights into the models and their suitability for policy design.

Chapter 6: This chapter presents the design of the “Transportation Energy Simulation Framework” together with an application of the framework to the larger metropolitan area of Zurich. The chapter also stresses the need for open source models in the area of electric vehicle modeling in order to facilitate interdisciplinary research collaboration.

Chapter 7: This chapter provides a summary regarding the results and highlights possible future work.

Although this is structured as a paper dissertation, meaning a collection of papers and book chapters first-authored by the PhD candidate, only minor repetitions are present. These repetitions are mostly related to the MATSim framework and are clearly identifiable as such and can be skipped when reading the entire dissertation.

Chapter 2

Performance Improvements for Large-Scale Traffic Simulation in MATSim

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Publication/Presentation

This chapter is based on a conference paper presented at the 9th Swiss Transportation Research Conference (Waraich *et al.*, 2009a). An extended and updated version of that paper is presented here.

2.1 Introduction

Traffic simulations can be performed at different levels of detail. One common technique is to model traffic as flows consisting of aggregated number of cars between different areas (Ortúzar and Willumsen, 2011). While this technique is quite fast, it does not allow modeling of individual preferences or temporally and spatially detailed analysis.

In contrast, *agent-based travel demand* models like MATSim represent each person in the simulation as an individual agent (MATSim, 2009). The travel demand by each agent in this case is based on an *activity-based* model, where activity times and durations are time dependent (Axhausen and Gärling, 1992). Furthermore a dynamic micro-simulation model is used to model detailed traffic interactions, which are again time dependent.

This enables various kinds of new applications, which are not possible with the first approach – e.g. detailed modeling of car sharing (Ciari et al., 2008) or modeling the charging behavior of electric vehicles (Waraich et al., 2009b). Also, commercial applications of such detailed micro-simulations can be envisioned. For example, companies owning advertising space could offer a more sophisticated service to customers, where not only the traffic volume along a road determines the price, but also the target audience of an advertisement is considered.

Whilst more powerful, such detailed micro-simulation models are more expensive, in terms of computation time, than aggregated models. This chapter describes efforts to improve the performance of an agent-based micro-simulation model, called Multi-Agent Transport Simulation Toolkit (MATSim, 2009). This model is aimed at the simulation of large travel demand scenarios. But, in order to perform a simulation of a full population run of Switzerland, with 7.3 million agents on a high-resolution navigation network, it is estimated that the existing Java-based micro-simulation in MATSim would require around 3 to 4 weeks. In the direction of reducing the computational time of MATSim, two of its central components are redesigned. The first component is the mobility simulation where the traffic dynamics are modeled. In order to make the mobility simulation faster, a new micro-simulation is implemented based on the ideas of an existing event-based micro-simulation (Charypar et al., 2007a). While multiple distributed and parallel traffic simulations in the C++ programming language have been implemented in the past (Barceló et al., 1998; Nökel and Schmidt, 2002; Nagel and Rickert, 2001), to the best of the authors' knowledge, this chapter presents the first large-scale implementation of such a simulation in the Java programming language (implemented mid 2009). Therefore, this chapter also discusses specific challenges for large-scale traffic simulation in Java, which has not been discussed in the related C++ literature.

A second major performance improvement achieved in this work is related to another core component of the MATSim framework, called event handling. This component is needed to process the results of the mobility system and is therefore essential for integration with other MATSim internal components, and also for extension of the MATSim model. Parallel computing is used to make event handling faster.

This chapter is structured as follows: in the next section, MATSim is described together with several mobility simulation implementations available for MATSim and open issues in this regards. Thereafter, the implementation of the various performance improvements with regards to the micro-simulation and the event-handling model are described. This is followed by experiments which assess the performance gains due to the newly implemented models. Before concluding, open issues are discussed together with possible future work.

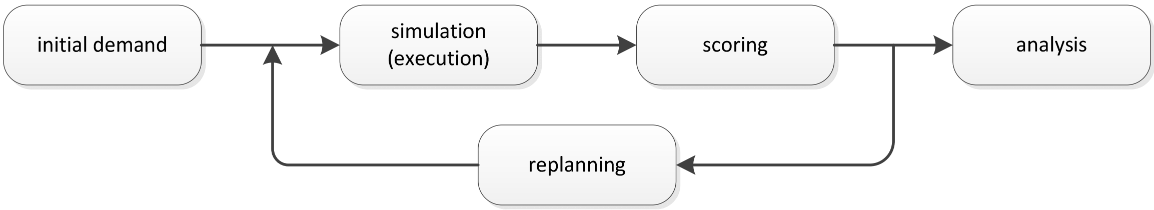
2.2 Related Work

In the following section, a description of MATSim is given, followed by a presentation of the different micro-simulation models and the event-handling module in MATSim.

2.2.1 MATSim

In MATSim individuals are modeled as agents, who want to perform activities throughout the day, such as being at home or work, and going shopping. But due to the spatial separation of the corresponding activity locations, agents need to travel. This leads to many additional choices for the agent, such as the mode of travel, the activity duration, the location and the route choice. The goal of MATSim is to find a plan for each agent, which maximizes the overall utility of the agent, including items as travel time, ticket fares or street toll prices. This optimization needs to be performed while keeping constraints of the agent’s environment in mind, such as street network capacities, or opening times at shops and working hours. This optimization of agents’ plans in MATSim is achieved by applying an iterative process, which is depicted in Figure 2.1.

Figure 2.1 Co-evolutionary simulation process of MATSim



In the beginning, the simulation starts with an initial plan for each agent, depicted as *initial demand*. A simple plan for an agent, who wants to leave home at 7:25 a.m. in the morning, work for 8 hours and 20 minutes, and then drive back home, might look as follows:

```
<plan>
     <act type="home" x="125" y="256" link="122" end_time="07:25:00" />

     <leg mode="car">
          <route> 122 19 59 </route>
     </leg>

     <act type="work" x="-500" y="100" link="59" dur="08:20:00" />

     <leg mode="car">
          <route> 59 10 7 122 </route>
     </leg>

     <act type="home" x="" y="0" link="122" />
</plan>
```

The plan also contains information about the road (link), where the home and work activities are located, and the route (link ids) the agent wants to drive. The micro-simulation in MATSim follows the instructions in the plan and executes it step by step. This means that the agent leaves home at the time specified in the plan and, thereafter, is routed through a virtual road network throughout the day. As an agent's vehicle is typically not travelling alone on the road network, interactions with other vehicles and road capacity constraints come into play. While the simulation is running, information about the performance of the plan is also collected. For example, did the agent need to pay a toll, how long was the travel time and how long did the agent work? This information is used to calculate different *utility* components for the various aspects of the plan. These are added up during the *scoring* step, such that each executed plan has a score assigned to it. The next step in the iteration is called *replanning*. In this step, either a plan, which was generated in a previous iteration, is reselected for execution in the next iteration or a new plan is generated, possibly by adapting a previous plan. This allows alternative choices for the agent such as the mode of travel or the travel route. Often, the probability of reselecting a plan for execution in the next iteration is based on its score, meaning that a plan with a higher score has a higher chance of reselection. Due to memory limitations, only a small number of plans are kept, and the plan with the lowest score is deleted whenever a new plan is generated. This corresponds to mutation, selection and survival of the fittest within the context of evolutionary algorithms (Holland, 1992). As this iterative process continues, the plans of the agents become more and more optimized, which is reflected by the improvement of the utility score of the agents over time. This score improvement flattens out after a certain number of iterations, depending on the choice dimensions available to the agents. This is interpreted as a situation, which is close to user equilibrium and is called optimized/relaxed demand.

After this brief description of the MATSim model, in the following section the different traffic micro-simulation models available for MATSim are presented in more detail.

2.2.2 Traffic Simulation Model

Traffic flow simulations range from detailed physical simulations to macroscopic models. Detailed physical simulation attempt to capture as many traffic flow phenomena as possible, e.g. car following and lane changing, by representing space continuously and simulating very small time steps, e.g. Fellendorf and Vortisch (2010). A second less detailed approach is represented by cellular automata, where car move between fixed sized cells, e.g. Nagel and Rickert (2001). Interactions between cars in neighboring cells are present, such that travel speeds and densities can be modelled disaggregated. The next less detailed level is present in mesoscopic models, where detailed traffic demand is present however only aggregated supply, e.g. Ben-Akiva et al. (1998). Macroscopic models represent the highest abstraction level, where supply and demand is modelled on an aggregated level, e.g. Cayford et al. (1997). For a more detailed literature review related to traffic simulations, see Charypar et al. (2007a).

There is a trade-off between computation time and model detail. As MATSim aims for large scale simulation, it uses a queue-based approach, which in terms of detail is located somewhere between the cellular automata and mesoscopic approach. While the details, in terms of implementation differ slightly, in general all of MATSim's traffic simulators consider roads as active elements, which move around cars. Each road link contains a queue which stores the entry time of each car. Adjacent links collaborate with each other to assure that link capacity, free speed travel time, intersection precedence and space availability are taken into account during the simulation. There are several implementations of the traffic simulation available, which are presented in the following section.

2.2.3 QueueSim and JQueueSim

The first micro-simulation developed for MATSim is called QueueSim and is based on a fixed-increment time advance model (Raney et al., 2003). In this model, vehicles are moved along links in fixed time steps of one second. Although the model is quite flexible, for larger simulations it is too slow because of the fixed simulation time step. A parallel version of QueueSim was implemented leading to a significant speed-up (Cetin, 2005). Both of these simulations are implemented in the C++ programming language. In order to improve the maintainability of the code, MATSim was later re-implemented in Java, including the non-parallel version of QueueSim, which is called JQueueSim here. In recent years, the performance of JQueueSim has improved, but the underlying simulation method remains the same.

2.2.4 DEQSim

A major performance breakthrough, within the MATSim context, is achieved with a more recent micro-simulation called Deterministic Event-Driven Queue-Based Traffic Flow Micro-Simulation (DEQSim, Charypar et al., 2007a), which is implemented in C++. Instead of performing the simulation along fixed time steps, an event-based model is used performing only discrete actions which are relevant to the model, i.e. entering and leaving roads. Furthermore, DEQSim has been parallelized making it one of the fastest large-scale transport micro-simulations currently available (Charypar et al., 2007b).

A major drawback of DEQSim within the MATSim context, is that it is implemented in C++, whilst the other modules of MATSim are implemented in Java. This means that the communication of DEQSim with the other MATSim modules is bridged by a slow file input/output (I/O) interface.

2.2.5 Graphical Processing Units

Yet a different approach to accelerate the micro-simulation was tried using Graphical Processing Units (GPUs) on computer graphic cards. These GUPs perform many more operations in the same amount of time than Central Processing Units (CPUs) on computer boards. A first successful implementation of QueueSim on GPUs rendered a speed-up of 67 times (Strippgen and Nagel, 2009) compared to JQueueSim. The main drawback of GPUs is similar to that of DEQSim, as the interface between the graphic card and the rest of MATSim modules poses a bottleneck. Furthermore, current GPUs have a limited amount of memory. For example, the traffic simulation of Switzerland, with 7.3 Million agents, requires around 60 GB of memory. Graphic cards today have often less than 4 GB of memory. Also, maintainability of the implementation is an issue, as the program code is not wirtten in Java.

In order to provide a faster micro-simulation in Java than QueueSim, here a redesign and re-implementation of DEQSim in Java is proposed, called *JDEQSim*. A second feature, for which an improvement is also proposed, is the event-handling module in MATSim, which is described in the next section.

2.2.6 Event Handling

The output of the traffic simulation contains detailed information about the course of the simulation. It describes e.g. when an agent's vehicle enters a road or arrives at an activity location. This information is embedded within a data structure called 'events', which contains information such as the identification of the agent, and the link where the event occurred and its time. These events are used to communicate the output of the micro-simulation to other modules in MATSim, such as scoring which can use it to calculate the performance score of an agent's plan. These events can also be utilized to extend the simulation, e.g. modeling the state of charge of the battery in an electric car or updating the capacity of a parking lot.

After their creation by the micro-simulation, events are handed over to the *event handler* module. Modules interested in certain types of events can register with the event handler. The event handler then processes each event according to the instructions of the registered modules.

It is clear that the performance of event handling is crucial to the performance of MATSim and its extensions. In the next section, the implementation of the JDEQSim and the performance improvements for the event handler are described.

2.3 Implementation

2.3.1 JDEQSim

The re-implementation of DEQSim in Java provided the opportunity to rethink and redesign its code structure. The C++ DEQSim code is used to understand the internal structure of the DEQSim traffic model but is not used for the implementation of JDEQSim itself. The design of JDEQSim is influenced by OMNeT++ (OMNeT++, 2009), which is a modular and open-architecture discrete-event communication-network simulator. To a certain extent, many elements used in JDEQSim are similar to concepts presented by Axhausen (1988).

The JDEQSim implementation consists of three parts: simulation units, messages and scheduler. Vehicles and links are the basic building blocks of the traffic simulation and are called *simulation units*. These simulation units communicate with each other by exchanging different kinds of *messages,* which can be thought of as internal events, which stay inside the traffic simulation. These are different from the external events, which are forwarded to the event handler by the micro-simulation. Each message contains a time stamp, e.g. when a vehicle is allowed to enter the next link or when a car should start a trip. Each newly created message is sent to the *scheduler*. The scheduler contains a message priority queue, which is ordered by message time and message type. At the beginning of the simulation, the end time of the first activity of each agent is scheduled in the queue. When the micro-simulation is started, the scheduler fetches the first message and delivers each message to its intended target simulation unit, where it gets executed, e.g. a car leaves one road and enters a new one. Often, execution of the instructions written in a message leads to the creation of new messages, which are then added to the queue of the scheduler. The processing of the messages also leads to the generation of external events, which includes the passing of these events to the event handler, where they are processed further. The scheduler will always only process the first message in the queue, until all of the messages have been processed and the micro-simulation ends.

As mentioned above, the messages are not only ordered according to time, but also according to the message type, which is not the case in most event-based simulations. This is required to solve the situation, in which two events happen at the same time and a causal order needs to be maintained. For example, it is logical that an agent first has to arrive home, before any activity can be performed there. Therefore, if the arrival at home, and the start of an activity there, happen at the same time due to a missing delay in-between, a priority needs to be given to the arrival event for it to be processed first. This is important both for the internal, and external consistency of the traffic simulation, including event handling.

Simulation of Transportation Modes besides Cars

While DEQSim only supports the simulation of cars, a simple and general model for other transport modes is present in JQueueSim. The model allows to define a constant travel speed for a new transportation mode. This model has also been implemented in JDEQSim.

Two other features, which distinguish the DEQSim and QueueSim model are described in the following section, as they have been implemented in JDEQSim.

Travelling Gaps in a Queue

When the front car in a traffic queue moves, it leaves behind a gap which travels backwards. Therefore, cars behind in the queue have to wait until such a gap reaches them before they can start driving. Such gaps, travelling backwards as a traffic queue is dissolving, are implemented in DEQSim (Charypar et al., 2007b). They have also been implemented in JDEQSim as this makes the model more realistic.

Prevention of Gridlock

A problem, which can occur in all of the micro-simulation models, is gridlock. For example, if links are full, and there is a circular flow relationship between vehicle movements on two or more links, it can lead to vehicles waiting for each other forever. In order to address this issue in DEQSim, if a vehicle waits for a long time at the front of a link, it is moved to the next link. This introduces a minimum flow at network links. Furthermore, the space available on a link is also temporarily modified.

An alternative to this mechanism could be to remove the agent and its vehicles from the simulation if it does not move after a certain maximum duration at the front of a road. This mechanism is implemented in JQueueSim, but has the disadvantage that, as the agent is suddenly removed during the simulation, the scoring of the agent and further processing is stopped. This measure is rather abrupt and can lead to temporary wrong results at modules processing events, e.g. wrong traffic counts. For this reason, the first approach to avoid gridlock is implemented in JDEQSim.

Besides the re-implementation and extension of DEQSim in Java, an attempt is also made to parallelize JDEQSim, which is described in the next section.

2.3.2 Parallelization of JDEQSim

In Charypar et al. (2007b), the parallelization of DEQSim is described. This is achieved by partitioning the traffic network into several pieces, which are assigned to separate CPUs of a shared memory machine. The Message Passing Interface (MPI, Snir et al., 1995) is used for communication between CPUs. When an agent travels from the network area assigned to one CPU to a different one, MPI is used for passing the agent's data between CPUs. This operation includes periodically synchronizing the state of links at the border of each network partition.

In Java, *threads* are used as a basis for parallel programming (Lea, 1999), where such instructions which need to be executed in parallel are distributed to different threads. In order to pass data between two threads, the *synchronized* keyword is used. The advantage of the Java synchronized keyword, compared to MPI in C++, is that no explicit data structures have to be built for transferring data between threads. This means that all data within the Java Virtual Machine (JVM, Lindholm et al., 1999) are accessible to all threads. But in the context of parallelizing JDEQSim, this turns out to be a major disadvantage; whereas MPI allows to explicitly specify which data to transfer between CPUs, it is not always obvious what data will be exchanged due to a synchronized statement in Java. While many elements of data transfer between threads are hidden and handled by the JVM, which simplifies programming, this also means that the programmer has little control over them for performance optimization.

Before describing a successful implementation of the parallelization of JDEQSim two straightforward, but failed, attempts in this regard are described. This helps to better understand the path taken and the various issues involved.

Failed Attempt 1: Single Scheduler Queue

As mentioned earlier, in Java each thread can access all data within the JVM. A simple parallelization solution is therefore to maintain a single scheduler queue within the JVM. The network links are assigned to different threads, e.g. using a network partitioning algorithm as used in DEQSim, such that most collocated links are assigned to the same thread.

In order to keep the state of the scheduler queue synchronized between threads, each access of the queue needs to be synchronized. Unfortunately, this leads to too many synchronizations between the threads, thus deteriorating performance. An attempt was also made to improve the performance by introducing message buffers, which are attached to the scheduler, but this did not help to resolve the problem.

Failed Attempt 2: Multiple Scheduler Queues

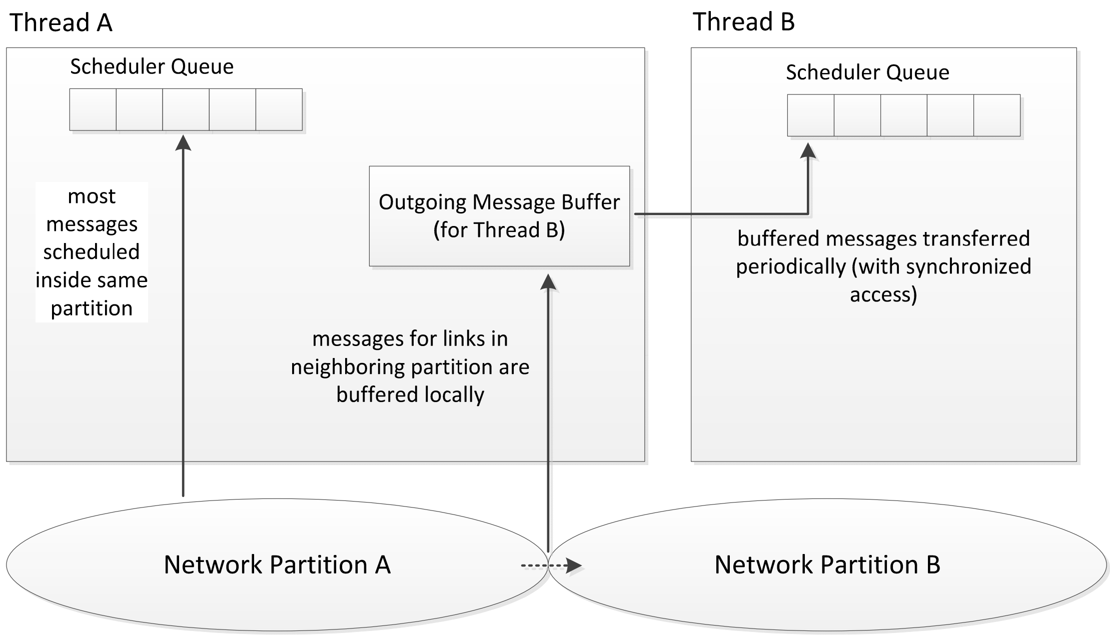
In order to try to solve the problem with the single scheduler queue, separate scheduler queues per thread are defined. Different threads still need to synchronize to ensure data consistency, e.g. when vehicles move between network partitions. Furthermore, periodical synchronization between border links at predefined intervals is needed to ensure that one thread does not advance the simulation too much. This synchronization interval is determined by the travel time needed to travel between two partitions. This method is almost identical to how the parallelization of DEQSim is performed.

Unfortunately, this approach does not perform well because of the periodical synchronization between threads and the waiting-time involved; whenever one thread is too far ahead, it has to wait on the other thread. This issue could be improved by applying a different method, described in the next section.

Successful Parallelization: Decoupling of Executor Threads

The main problem detected with the multiple scheduler queues approach is that the synchronization between threads happens too often, thus hindering parallelization. A new approach in this regard is implemented which successfully decouples the threads, as shown in Figure 2.2. Instead of periodically synchronizing between network partitions on a link level, as in DEQSim, a periodic synchronization for the whole partition is performed periodically after a fixed interval δ. This means that all messages generated during this interval, which need to be added to the scheduler queue of an adjacent network partition, are buffered and then added at once using synchronized access. The maximum allowed δ between two threads is determined by the link with the shortest travel time, which resides at the border of the two network partitions. As a larger δ is better for simulation performance, possible adaptations to the network portioning algorithm are discussed further in the future work section.

Figure 2.2 Parallelization of JDEQSim

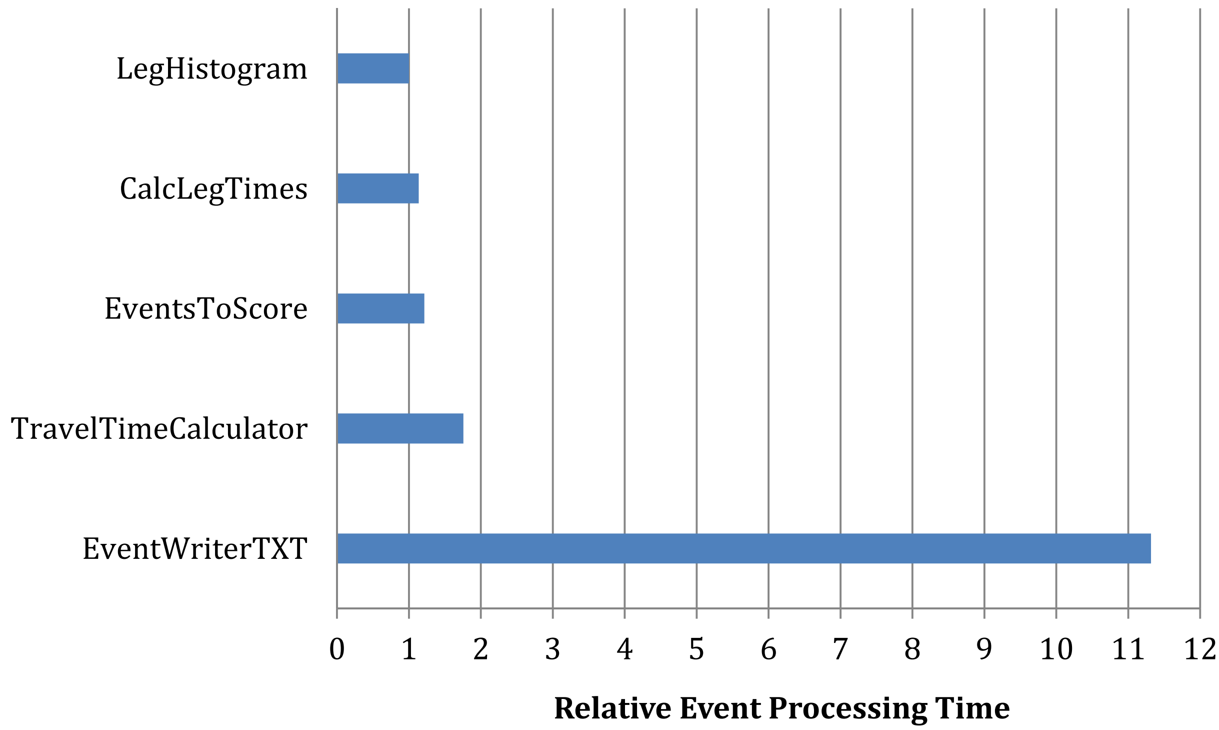


2.3.3 Parallel Event Handling

During the development of JDEQSim and its parallelization, it was observed that event handling is executed on the same thread as the micro-simulation itself. But as the event-handling process is independent of the micro-simulation, and can be further split into multiple event handling tasks, it is ideal for parallelization. Such a parallelization allows us not only to run the micro-simulation faster, but it also improves the performance of extensions of MATSim, which use the event handling interface.

Currently, five default event handlers are present in MATSim. Figure 2.3 shows the relative time proportions of these five handlers to each other. Two of these event handlers are needed for gathering and communicating information between the micro-simulation and other MATSim modules: *EventsToScore* for accumulation of the utility score components and *TravelTimeCalculator* for estimating the travel time. Two additional event handlers generate statistics and graphs of the simulation (*LegHistogram* and *CalcLegTimes*). The most time-consuming event handler is *EventWriterTXT* which writes all events produced by the micro-simulation to a file, allowing later post processing and analysis of simulation results.

Figure 2.3 The execution time of default event handlers



Implementation

The parallelized version of event handling is called parallel event handling and allows the user to specify how many threads should be dedicated to this module during the simulation. The current implementation applies a round-robin approach (Hahne, 1991) to assign event handlers to threads. This means it tries to assign the same number of event handlers to each thread. It is obvious from Figure 2.3 that this approach is suboptimal, because it would be best to put the event handler writing out events to a separate thread and the other handlers on a second one.

Fortunately, writing out events to a file is not part of the communication interface between JDEQSim and MATSim, which is different in DEQSim. This means the event file is needed only in the last iteration as a backup for further analysis. Additionally, events can be written out at predefined intervals, e.g. each 10^{th} iteration, in order to analyze intermediate results of a bigger simulation, while it is still running. This means during most iterations a quite balanced parallelization of event handling is possible using up to 4 cores if considering the default simulation without any other scenario specific event handlers.

While the implementation of parallel event handling could be improved in several ways, as discussed in the future work section, the reason to start with a simple implementation is that the existing interfaces did not need to be changed.

2.4 Experiments and Results

2.4.1 Single Thread JDEQSim with Parallel Event Handling

While the parallel version of JDEQSim is still experimental work, the non-parallel version of JDEQSim is planned to be run with parallel event handling in near future for large-scale scenarios[1]. Therefore, experiments presented here are conducted in the latter configuration, to demonstrate the performance gains, when comparing it to the current state of the art micro-simulation in Java (JQueueSim). Furthermore, the performance gains due to parallel event handling are also demonstrated. While the focus is on a comparison of JDEQSim with JQueueSim, runs with DEQSim are also conducted for reference.

Scenario Setup and Hardware

The simulations are conducted on a NAVTEQ road network (NAVTEQ, 2009) for Switzerland, with around 882K links. A population sample of the

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[1] Have been conducted in 2010 (see, Meister et al., 2010).

people surrounding the city of Zurich who drive cars is used, containing around 614K agents. The hardware used for this experiment is a Sun Fire X4600 M2, with 16 cores (8 dual core CPUs) and 128 GB of memory. Due to the large number of simulations, not all runs could be repeated multiple times. To give a sense of the variability of the JDEQSim results, for a similar JDEQSim run over 50 iterations, the standard deviation for the computation time amounted to 13% of its mean value (for micro-simulation and event handling).

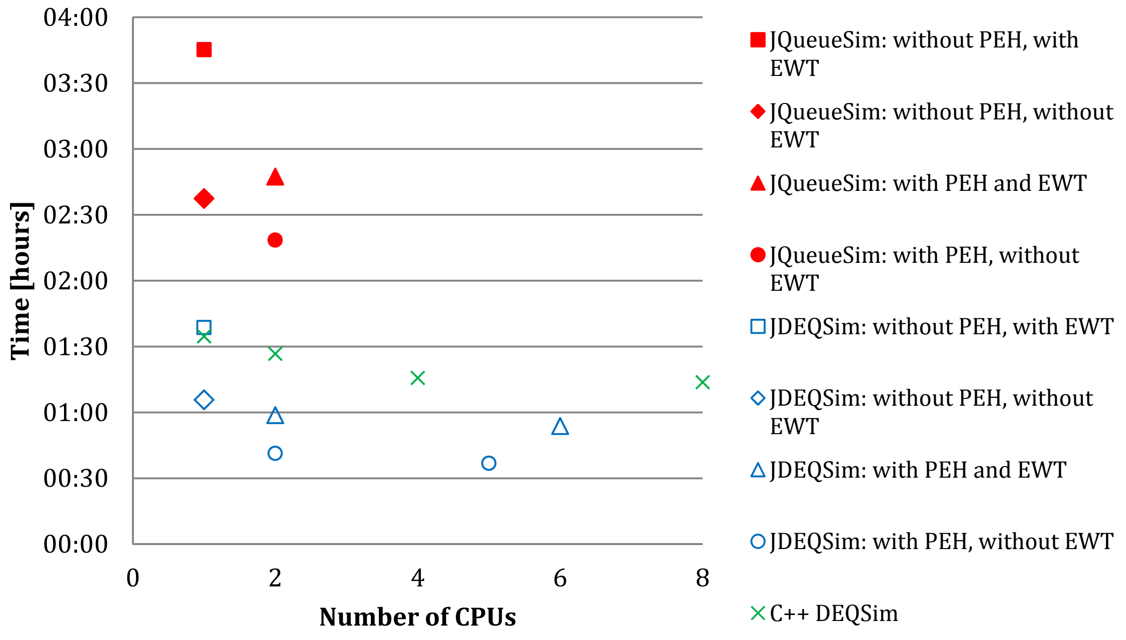
Runtime: Micro-Simulation and Event Handling

In the first experiment, the runtime of the three mirco-simulations is compared using nine configurations, where also the number of threads used are varied (see Figure 2.4). Configurations include runs with and without parallel event handling (abbreviated as PEH in Figure 2.4). Furthermore, runs with, and without, the EventWriterTXT event handler are conducted (abbreviated as EWT in Figure 2.4).

Both JDEQSim and JQueueSim runs with a single thread use the default event handling, while runs with more than one thread use parallel event handling. For example, the JDEQSim run with two threads uses one thread for the micro-simulation and one for parallel event handling. In the DEQSim runs, first the micro-simulation is run using the indicated number of threads, thereafter the events are written to a file and read in by the non-parallel version of the event handler for further processing.

The number of threads usable in the different configurations cannot be chosen arbitrarily: The number of threads ‘n’ which can be used by DEQSim is constrained to $n=2^i$, where $i \geq 0$. This is due to the network partitioning algorithm used. For JDEQSim, the maximum number of usable threads in the presented scenario is five without EWT and six with EWT. In these cases one thread is used for the micro-simulation and one thread for each of the default event handlers. However, only a selected number of configurations and thread combinations are simulated and discussed here.

Figure 2.4 The computation time for the three micro-simulations as a function of number of threads



The first two configurations look at JQueueSim without PEH and with and without EWT. The comparison of these two configurations highlights the overhead due EWT (43%). Configuration three and four look at JQueueSim for the case where PEH is turn on, again with and without EWT. The experiments show that the newly implemented parallel event handling reduces the time of an iteration by around 26% for the case where writing events out is turned on (configuration one vs. three) and by around 13% for the case where writing out events is turned off (configuration two vs. four). The higher gain for the case where events are written out to the hard drive is expected, as in this case parallel event handling successfully decouples the micro-simulation from I/O operations.

The configurations one to four and five to eight correspond to each other, only in the later uses JDEQSim instead of JQueueSim. In order to measure possible performance gains due to the implementations made in this chapter, JQueueSim and JDEQSim need to be compared for the case where writing out events is turned off, and the latter uses PEH (configuration four vs. eight). The reason for comparing the case where event writing is turned off is important, because in most iterations this configuration is run. In this case, the runtime is reduced by around four times for the given scenario. The major part of this speed-up (ca. 76%) is due to the differences in models of JDEQSim and JQueueSim (event-based vs. fixed time steps). This can be seen when comparing configuration two and six where only a single thread is used both for JDEQSim and JQueueSim. The remaining performance gain is due to the parallelization of event handling (configuration six vs. eight).

Configuration nine shows DEQSim runs for various numbers of CPUs used. While the runtimes of JDEQSim and DEQSim are similar, when PEH is not used and EWT is turned on (configuration five vs. nine), already turning off EWT leads to a major performance gain for JDEQSim compared to DEQSim (50%, compare configuration five vs. six). This gap between DEQSim and JDEQSim even builds up further, when turning on PEH, such that JDEQSim always performs better than DEQSim up to eight CPUs (configuration seven/eight vs. nine). Furthermore, as the flattening of the runtime curves suggests, it might be quite difficult for DEQSim to reach a runtime lower than that of JDEQSim, even if using a higher number of CPUs as is explained using Amdahl's law in the next section (Amdhal, 1967).

Amdahl's Law and its Implications

Amdahl's law describes the maximum achievable speed-up of a parallel program. It says that, if a certain portion of a program cannot be parallelized, then the maximum achievable speed-up is limited – even with unbounded computation power. The maximum achievable speed-up with *n* threads for a program, where *b* percent of the program cannot be parallelized can be calculated using Equation (2.1).

$$S(n) = \frac{1}{b+\frac{1-b}{n}} \quad (2.1)$$

To give an example of Amdahl's law: if 5% of a program cannot be parallelized, then it is not possible to achieve a speed-up of more than 20. The implication of Amdahl's law is present both for DEQSim and JDEQSim runs, but at different points. For DEQSim, the interface between the micro-simulation and MATSim is the bottleneck. Because of the I/O overhead of the communication between the micro-simulation and MATSim, a speed-up of even two seems impossible. This means that more than 50% of the micro-simulation consists of parts which have to be executed sequentially. A second and smaller part, of non-parallelizable code present in the DEQSim runs, is the event handling, which cannot run in parallel mode for DEQSim at the moment. In case of parallel event handling the maximum achievable speed-up is limited by the slowest event handler.

This first experiment suggests that to make most efficient use of CPUs, JDEQSim should be run with one parallel event-handling thread. As the machine used in this experiment has around 128 GB RAM and 16 cores, and the scenario uses less than 15 GB of RAM, several JDEQSim runs could run in parallel, which is useful especially during the calibration phase.

2.4.2 Influence of Network Size

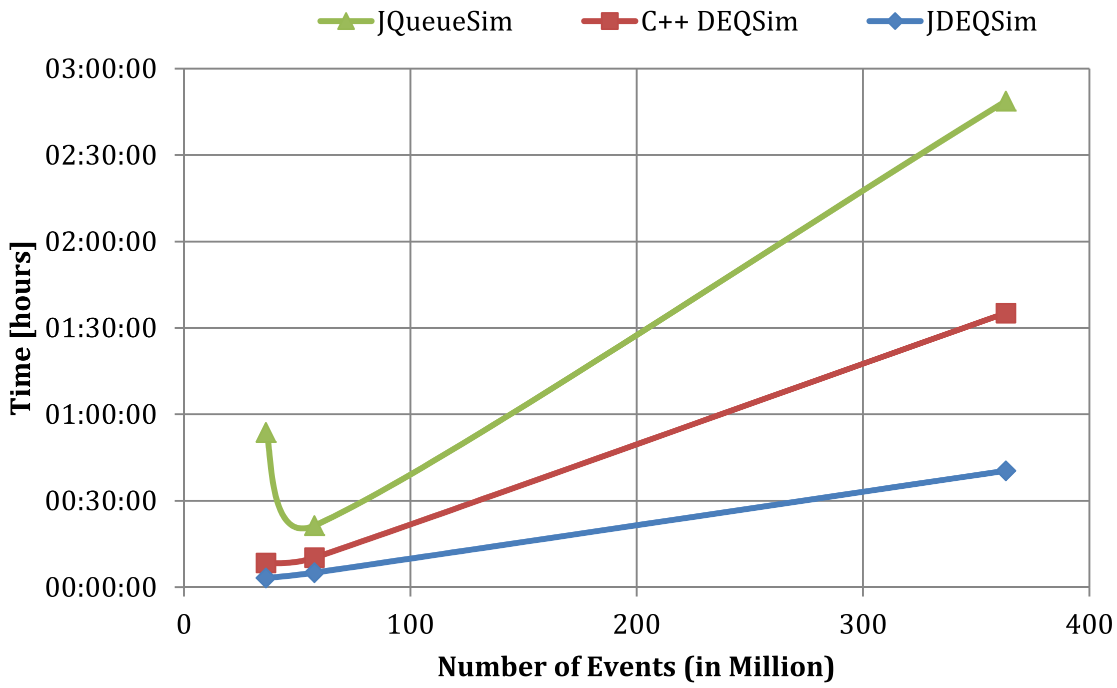
In the previous experiment, JDEQSim performed around four times faster than JQueueSim. But this cannot be generalized, because if the network is congested, then JDEQSim can be much faster than JQueueSim. Such congestion can happen especially during the initial iterations, in which the routes are far from optimal and can lead to a simulation period stretching far beyond 24 hours. This can lead to long run times for JQueueSim as its runtime is directly correlated to the simulation period.

Furthermore, different ratios of network size and population can widen the gap between the speed-up of JQueueSim and JDEQSim, which is highlighted here. In this experiment, all micro-simulations are run using two threads. Both JDEQSim and JQueueSim runs are performed with parallel event handling, using a single thread and no events are written to the hard drive. The network capacity is chosen in such a way that no congestion should happen in order to remove possible adverse influence of this on JQueueSim. The three scenarios which are considered are:

- Scenario A: Network with 882K links and 61K agents (36M events)
- Scenario B: Network with 61K links and 616K agents (58M events)
- Scenario C: Network with 882K links and 614K agents (363M events)

This results of the experiments in Figure 2.5 show that DEQSim and JDEQSim scale linearly with the number of events. Only in Scenario A, in the case of DEQSim, the I/O overhead of loading the network is immense compared to the actual simulation time.

Figure 2.5 The influence of network size on the three micro-simulations



For JQueueSim the situation is different. While Scenario A and B generate the same magnitude of events, the run times are substantially different. This has to do with the substantially different ratio of network-to-population size. Therefore, in Scenario A, JQueueSim performs extremely badly compared to JDEQSim. In fact, JDEQSim is more than 17 times faster than JQueueSim in Scenario A, while for Scenario B and C it is around four times faster.

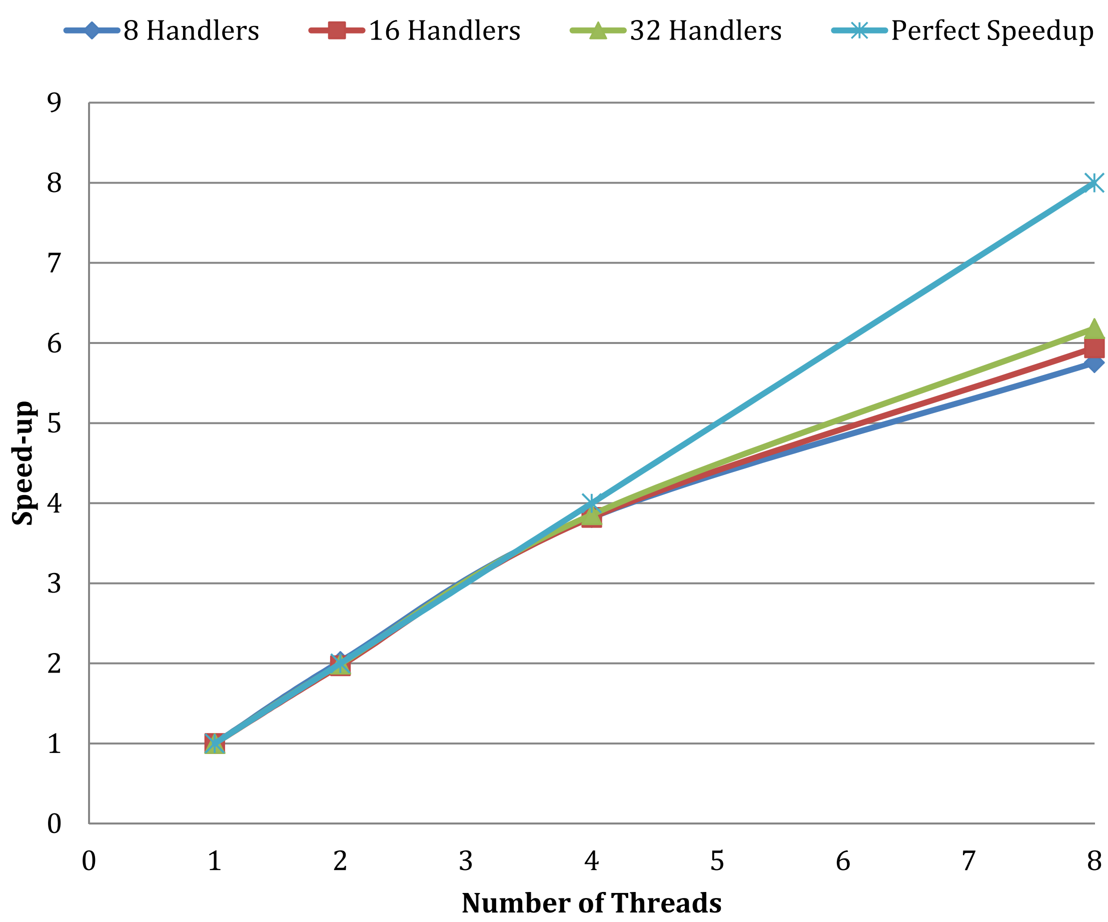
2.4.3 Scalability of Event Handlers

While the first two experiments look at the overall performance increase, due to both the micro-simulation and parallel event handling, in this section we only look at the latter. As mentioned earlier, the event handler with the longest computation time defines the runtime of parallel event handling. Therefore, in order to test how parallel event handling would scale with multiple event handlers and threads, identical test handlers are added to the simulation. The test handler performs computationally intensive tasks and does not involve any disk I/O. This is important because event handlers requiring I/O are inherently difficult to parallelize due to the speed limit of the hard drive, and are therefore not suitable for this experiment.

Figure 2.6 shows the speed-up for the different runs, where different numbers of handlers are involved. This experiment shows that parallel event handling scales linearly up to 4 threads, but the speed-up with 8 threads already drops to around 6. This drop is severe if we consider that only little use of Java's synchronized keyword is made. Even complexer parallel programs written in C++ with MPI achieve speedups of around 8 in this case (Charypar et al., 2007a).

While only a small number of event handlers are present by default in MATSim, many applications are under development and planned in the MATSim community (MATSim, 2009) which require additional event handlers. The good news is, that if more handlers are added to parallel event handling, the speed-up gets slightly better, as can be seen in the 8-thread scenario. This is expected, because adding more work to the handler reduces the relative penalty of synchronization between threads.

Figure 2.6 Performance of parallel event handling



2.4.4 Speed-up for Parallel JDEQSim

As described earlier, a first prototype of the parallelization of JDEQSim for two threads has been implemented. As event handling has not been adapted yet to properly function with parallel JDEQSim, only measurements of the micro-simulation are reported here where event handling is turned off. The experiment consists of 1.62 million agents residing in the surroundings of Zurich city. The network contains 163K links. This experiment required 29 minutes and 40 seconds when running with JDEQSim, while on the parallel JDEQSim (2 threads), the experiment only took 18 minutes and 37 seconds. This is a speed-up of 1.6, which is encouraging, but many problems remain unresolved, as is discussed in the future work section.

2.4.5 Simulation of Switzerland

One of the near-future goals of the performance improvements presented in this chapter is to perform simulation runs for the whole of Switzerland, therefore, a first experiment in this direction is conducted. This experiment simulates the whole population of Switzerland (7.3 million agents) on a network with around one million links. The agents travelled using different transportation modes, such as by car, bus, bike and on foot. The experiment is run with the single threaded version of JDEQSim and parallel event handling with a single thread. It took around 3 hours and 16 minutes for a single iteration of micro-simulation and event handling, while for replanning and the rest an additional 70–80 minutes are needed. As MATSim is an iterative process, depending on the search space, many iterations are needed to reach a relaxed state (Balmer et al., 2009). When only route choice, mode choice and departure time/duration adaption are enabled, around 60 iterations are required (based on experience). It is estimated that it may take around 11 days for these 60 iterations to complete, considering that the overhead of writing out events to the hard drive is only conducted each 10th iteration. If we assume a speed-up of four for JDEQSim compared to JQueueSim and also take the computational time of the other modules into account, it is estimated that with JQueueSim it would take around 36 days to calculate such a scenario. This is a speed-up of around 3.2 for the overall simulation. This means, whilst the performance gains achieved by the work presented in this chapter are important, still more progress related to performance is needed, which is discussed in the next section.

2.5 Discussion and Future Work

Whilst two ways to significantly shorten the runtime of the MATSim simulation are presented in this chapter, it seems like the 'low hanging fruits have been picked' and additional improvements will not be as straight forward and may possibly lead to not as much performance improvement, as well as requiring major changes to the existing models and interfaces. In the following section, issues involved are discussed together with possible solutions.

2.5.1 Parallel Micro-Simulation

In order to achieve a major breakthrough with regards to the micro-simulation performance, making use of multiple threads seems to be crucial. Although a first success in direction of a parallelization of DEQSim has been made, a successful integration of this into MATSim needs more work and would also require fundamental changes to the existing models.

Two points seem central to a successful integration of parallel JDEQSim in MATSim: decoupling of threads and integration of parallel JDEQSim with parallel event handling. In both cases also synchronization overheads between threads in Java contribute to the increased computation time which is further discussed in the following sections.

Load Balancing

For decoupling of different micro-simulation threads, the workload needs to be distributed evenly among them and the time period δ for two periodical synchronizations between threads should be as long as possible.

For assigning the same amount of work to all threads, currently the network is partitioned at the beginning of the iteration. However, as traffic load changes over the day, this may lead to a major imbalance of workload among threads during the course of the iteration. This causes faster threads to wait on slower ones due to the periodic synchronization. This situation could be improved by changing the network partition assignment to threads during the iteration to correct for the imbalance. This operation could be performed at the time when synchronization between threads happens.

Besides the workload, the coupling of two threads is affected by the time period δ after which two threads need to synchronize. This time is determined by the link with the shortest travel time at the border of two network partitions. Therefore, a way forward might be to partition the network in a way which maximizes the duration between two consecutive thread synchronizations. But it is unclear how much coupling between threads is caused due to an imbalance of workload between threads, and how much improvement could be achieved by partitioning the network, in a way that δ is maximized. Therefore, extensive experiments would be required in this regard to be able to make recommendations on how to proceed in this regards.

Trade-off: Preciseness vs. Performance

If the synchronization time period between two threads is above its maximum value (defined by the link with the shortest travel time at the partition border), race conditions will occur, meaning that cars at the border links could enter the neighboring partition too early or too late, leading to a distortion of traffic patterns. It would be interesting to investigate up to what value of δ a significant performance increase can be achieved and how much the traffic patterns are affected due to this. According to initial experiments in this regard, a possible trade-off between preciseness and performance could be a viable way to increase performance.

Adaptation of Event Handling

The events processed by event handling must have an ascending time stamp. However, this is not naturally the case when events are generated by different threads of the parallel micro-simulation. Therefore, neither the current single-threaded event handler, nor the new parallel event handler, are suitable for use with the parallel version of JDEQSim. Buffering and sorting of events needs to be implemented between the micro-simulation and the event handler, in order to make this possible.

In the following section, additional issues and possible improvements related to event handling are discussed.

2.5.2 Event Handling

Performance

According to the experiments conducted, parallel event handing scales well if the load is well balanced. But this is often not the case when one or several event handlers involved contain many disk I/O operations. In this case, these event handlers pose a bottleneck to the current parallelization approach in several ways: firstly as I/O operations are slow, event handlers involving many I/O operations are the slowest event handlers; secondly, as writing to hard disk is limited by the speed of the hard disk, this becomes even more of an issue because such handlers slow each other down even further or might even be influenced by other I/O operations on the same computer.

In order to solve this problem, one might distinguish event handlers based on the criteria if other modules in the simulation depend on their output. Only such modules which fulfill this criteria require that event handling is completed before the next step in the MATSim loop is executed. Of the five default event handlers, this is only the case for two of the event handlers (EventsToScore and TravelTimeCalculator). The other three event handlers only produce output for later analysis. This means that these three event handlers could continue their processing, while the rest of the MATSim iterations continue. This approach could certainly be used to reduce the overall computational time of MATSim.

A second performance improvement could be achieved by replacing the current round-robin algorithm, which assigns an even number of event handlers to all threads with one which performs better load balancing. This could be achieved in the following way: the average runtime of the different event handlers could be tracked and a load balancing could be performed, every couple of iterations, while taking this information into account.

Usability

While event handling is a simple way for users to access the output of the MATSim simulation and also to extend the simulation itself, with parallel event handling and other performance improvements, the possibilities of making errors especially for novice users of MATSim increases.

A possible pitfall of using parallel event handling could arise in the following way: while with non-parallel event handling, it is not a problem if different event handlers access each other's data, this could cause race conditions in the case of parallel event handling. This means that if no synchronization is used, data written by one thread could not be visible to another thread and, as such, data inconsistencies could occur. While the default event handlers are all implemented in a way that this problem cannot occur, users not familiar with the intricacies involved could make such a mistake.

Also, the proposed performance improvement – where a distinction between event handlers is made, whether they produce output for other MATSim modules or not – adds to the complexity of how event handling is used till now. This means that there is a trade-off between usability and performance with regards to parallel event handling of which users need to be informed of.

2.5.3 Replanning Modules

Besides the micro-simulation and event handling, replanning is the third module in MATSim which requires major computational time. Besides reducing the computational time of the various modules involved, e.g. routing, such work is also important which helps to reduce the number of iterations required to reach a relaxed state. Therefore, ongoing work related to Meister et al., (2006) seems to be important in this regard, where new optimization methods and heuristics are applied in order to reduce the number of iterations.

Another research strand to investigate is by how much the runtime can be reduced by making more dynamic use of the replanning module than at the moment. Currently, the probability for applying a replanning strategy in MATSim is fixed at the beginning of the simulation. For example, in each iteration 10% of the agents try to reroute. Whilst systematic research in this regard is limited, experience suggests that some search dimensions do not need a constant replanning share throughout the simulation. For example, the share of rerouting could be reduced over time, as optimal routes are often found within the first 10–20 iterations with a 10% reroute share. This could accelerate the overall simulation as the freed up processing power could be used by other replanning modules.

2.6 Conclusions

This chapter presents to the best of the authors' knowledge the first implementation of a large-scale traffic simulation in Java, while making use of parallel computing. Therefore, several issues discussed in this chapter have been raised for the first time in traffic simulation literature and might be useful for the implementation of other traffic simulation models in Java as well.

The main contribution of this chapter is that two methods are proposed and implemented to improve the performance of the agent-based travel demand simulation MATSim. This is achieved by improving the performance of the micro-simulation and by parallelizing the processing of its output. As a result of these performance improvements, larger runs can be simulated in less time and using fewer CPUs/cores than has been possible until now.

Experiments show that, through the proposed improvements, the runtime of the current Java based micro-simulation is improved by a factor of four and more, depending on the scenario. As MATSim is aimed at the simulation of large-scale scenarios and simulation runs of whole of Switzerland are planned in near future on high-resolution networks, it is shown that the computational time for the whole MATSim run is reduced by a factor of around 3, to about 4.5 hours per iteration.

Whist this is a significant performance improvement, further improvements of various modules of the MATSim simulation are also proposed, especially with regards to the parallelization of the micro-simulation.

Chapter 3

Plug-in Hybrid Electric Vehicles and Smart Grid: Investigations Based on a Micro-Simulation

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3.1 Introduction

These days, fossil fuels are the most important primary energy source in most countries of the world. The transportation sector and individual transport in particular is highly dependent on fossil fuels. For several reasons, endeavors are undertaken to break this dependence. Reasons include concerns about the economic and political implications of the current use of limited fossil resources or the impact of greenhouse gases on climate change. One solution to these problems could be the electrification of vehicles. It has been estimated that electrifying the whole transportation sector could shrink energy consumption to one fifth of current consumption (MacKay, 2009). Moreover, driving with electricity is currently far less expensive than driving with gasoline (IEEEUSA, 2007). In addition, electrifying the transport sector would promote sustainable ways of generating electricity, such as wind and solar energy (Short and Denholm, 2006). Also, there are advantages for the air quality and human health, such as reduction of particulate pollution and acid rain (Sovacool, 2010).

3.1.1 Plug-in Hybrid Electric Vehicles

Although EVs have been available for quite some time, their limited range has hindered their widespread use. Plug-in hybrid electric vehicles (PHEVs) can run on both electricity and gasoline. The batteries of these vehicles can be charged at home or at other locations by means of an ordinary plug. As most people generally drive short distances during the week (BFS, 2006), the vehicles would mainly run on electricity. Only during longer trips would gasoline be used when the vehicles' batteries became depleted.

The introduction of PHEVs might also create the demand needed for companies to invest in electric fuel stations (Bradley and Frank, 2009). This would also foster the introduction of EVs, which vitally depend on such an infrastructure.

3.1.2 Smart Grid

For electric power generation and distribution utilities, the ability to predict the demand for electricity during the day is vital, because this ability directly influences the operation of the system and hence revenues as well as the security of supply. A shift to electric vehicles would increase the demand for electricity. Furthermore, the demand for electricity from these cars would be dynamic in terms of time and location. This can lead to multiple challenges for the electricity system. An increase in peak load demand could cause the need to utilize more expensive generation units, if available. Furthermore, presuming the electricity generation capacities are sufficient, the electricity network's physical constraints could be violated by the additional PEV demand at the medium- and low-voltage levels (Lopes *et al.*, 2009). A possible solution to this problem could be offered by a future smart grid (National Energy Technology Laboratory, 2007).

The idea of a smart grid is to use advanced information and communication technologies in order to intelligently manage the provision of electrical energy to consumers. This means that by consolidating data from different sources (e.g., conventional generators, renewable energy producers, consumers, network operators and PEVs), the demand and supply are matched in a way to ensure network security and system sustainability. For instance, PEV owners and electric utilities could sign an agreement according to which vehicle charging could be stopped for a few minutes during demand peak times. In turn, the vehicle owners would receive compensation from the utility company or responsible entity. The general role of PEVs in such a future smart grid environment is elaborated in Galus *et al.*, (2012a,b).

3.1.3 Vehicle-to-Grid Technology

Through the use of a smart grid, the Vehicle-to-Grid (V2G) concept could become reality (Kempton and Tomic, 2005). A V2G implementation allows PEVs to act as resources to the grid. There are various potential applications for V2G technology (Kempton and Kubo, 2000; Galus *et al.*, 2012a,b): If the demand for electricity in the grid exceeds the supply during peak hours, PEVs could supply peak power. There are also applications in which the vehicles are used to balance the power in feed prediction error of renewable energy generators (Kempton and Dhanju, 2006; Galus and Andersson, 2012), or where they provide ancillary services to the electric grid in order to stabilize the network (Galus *et al.*, 2011).

This chapter presents the initial version of a framework, which helps to analyze the interaction of emerging technologies in connection with PEVs (e.g. smart grid). This framework is able to uncover limitations of existing electricity grids for potential future electricity demand of PEVs. The developed framework is able to analyze differing charging policies and their impact on transportation and electricity networks. Therefore, this framework can also be used to design charging policies for PEVs, which help balancing the electricity demand and planning of PEVs infrastructure (e.g. charging stations).

In the following section, related work is presented together with the two systems on which the framework is based. Then, the methodology and subsequently the experiments are described. Before presenting the conclusions, an outlook on possible future research is given.

3.2 Related Work and Background Information

Several studies have been conducted regarding the energy consumption of PEVs and their influence on the electric grid. Some of the most recent and relevant work to the topic of this chapter is summarized in the following.

Lopes *et al.* (2009) demonstrate the impact of electric vehicle charging on medium voltage distribution grids. The results point to the appearance of various bottlenecks in the electrical network, such as excessively low voltage and transformer and line capacity violations. In their study, fixed durations (e.g., 4 h) are assumed for electric vehicle charging.

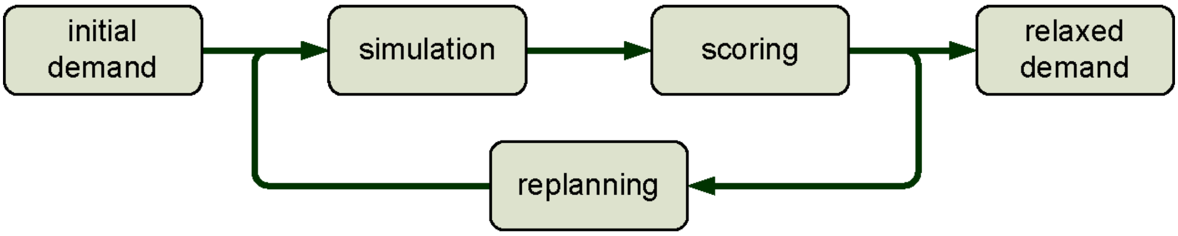
In Letendre *et al.* (2008) and Letendre and Watts (2009) an accumulated energy model is used to show that a large number of PEVs could be accommodated by the utility grid in Vermont if PEVs are charged during the night. Furthermore, the potential number of cars which could be accommodated by a smart grid is estimated. For the experiments, the charging time of the PEVs is fixed to 6 h. The arrival times of the cars are uniformly distributed between 8 a.m. and 9 a.m. at work locations and between 6 p.m. and 8 p.m. at home locations.

The chapter at hand also presents several PEV charging schemes. In contrast to the above-mentioned papers, the charging times and locations of the vehicles are based on an activity model of drivers. Therefore, the vehicles' energy consumption and charging durations are not constant. Furthermore, an electricity grid and a gas network are interconnected and model a possible future energy infrastructure that offers much flexibility and diversity. The electric networks incorporate physical constraints for the power flow. In the following two sections, both, the mobility model used for the transportation simulation and the energy system are described.

3.2.1 Multi-Agent Transport Simulation (MATSim)

Traffic simulations can be performed at different levels of detail. One the one hand, traffic can be modeled as flows consisting of an aggregate number of cars; on the other hand, it can be modeled as individual vehicles. A simulation in which each car owner is an agent is called an “agent-based micro-simulation”; it allows vehicles to be tracked dynamically over time. MATSim (MATSim, 2009) is such an agent-based micro-simulation with focus on large scenarios. Simulations with more than seven million agents in a navigation network containing around one million links have already been implemented using MATSim (Charypar *et al.*, 2007a; Waraich *et al.*, 2009a; Meister *et al.*, 2010). Vehicle owners in MATSim are modeled as agents. Figure 3.1 shows the MATSim simulation process: Each agent has a daily plan of trips and activities, such as going to work, to school or shopping. The agents’ daily plans, the street network and the facilities are modeled in the initial demand (Balmer, 2007). The plans of all of the agents are executed by a micro-simulation, resulting in traffic on roads and perhaps traffic jams (Cetin, 2005; Charypar *et al.*, 2007b).

Figure 3.1 Co-evolutionary simulation process of MATSim.



The execution of each plan is scored and assigned a utility. For example, a person with a lower travel time has a higher utility than one whose travel time is longer because of a traffic jam. Furthermore, work (earning money) and other activities increase the utility. The goal is to maximize the utility of each agent’s daily plan by replanning the day based on a coevolutionary algorithm (Holland, 1992). Such an algorithm generally tries to find a maximum fitness function (here, the utility function) by using crossovers and mutations. In the MATSim context, the utility function has several degrees of freedom, such as the routes, working hours, travel mode chosen, locations visited, and so on. It can also be extended to include the energy consumption of the vehicles. The daily plans are evaluated, and bad daily plans (plans with a low performance or low utility) are deleted, which corresponds to the survival of the fittest function in co-evolutionary algorithms. New plans are then generated based on the results of the previous set of plans. The cycle of executing all plans, scoring and replanning them is called an iteration. The simulation is an iterative process which approaches a point of rest corresponding to a user equilibrium called relaxed demand.

The relaxed demand can then be analyzed. More details about the conceptual framework and the optimization process of the MATSim toolkit can be found in MATSim (2008).

One of the reasons for using an agent-based approach instead of an aggregate one is that individual agent preferences (e.g. when or where to charge the PEV) can be modeled based on the utility function. Furthermore, simulating the constraints of the electric network requires detailed data regarding locations and times of electricity demand. In MATSim, high-resolution road networks, including individual buildings, can be simulated, which makes a mapping to the underlying electric grid infrastructure possible.

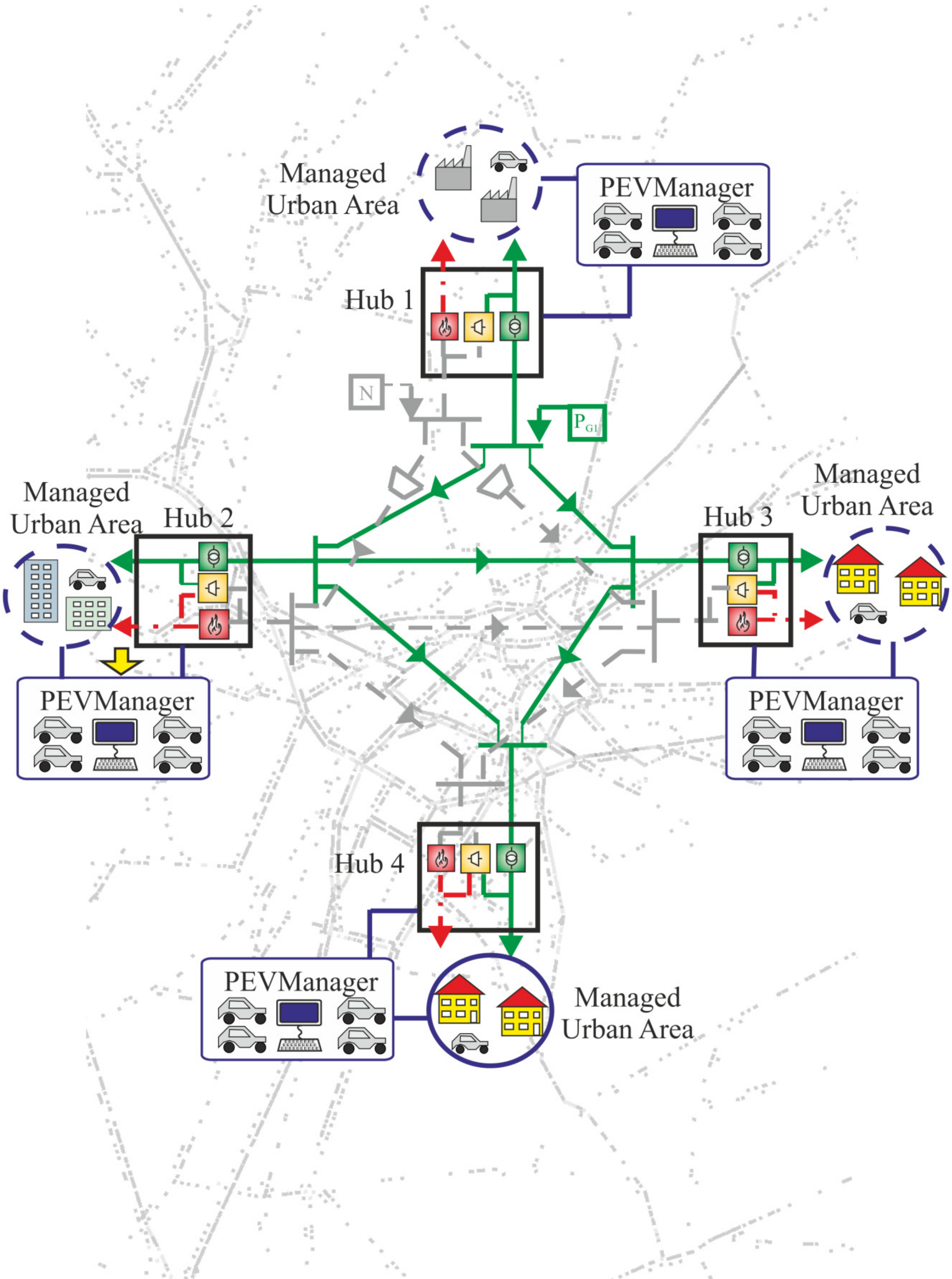
3.2.2 PEV Management and Power System Simulation (PMPSS)

Figure 3.2 depicts the power system used in the following. It contains multiple energy carriers. Each node in the power network is modeled by an energy hub. Energy hubs interconnect multiple energy carriers in order to optimize the supply of the consumers' demand. They are elaborated in Geidl and Andersson, 2005, and their application in networks is described in Geidl and Andersson, 2007 and del Real *et al.*, 2009. Each hub should be understood to model an urban area, e.g., a residential, business or industrial area. Real electricity load curves are used to model the demand for the particular area. The hubs contain a furnace to meet the heat demand, a transformer to supply electricity and a small combined heat and power (CHP) turbine. The CHP interconnects the electricity and gas networks and can relieve the electricity networks.

The electrical power lines (Wollenberg and Wood, 1996) and gas lines (Menon, 2005) are modeled according to physical laws. The system can thus be understood to model a potential future energy system, because the share of distributed power generation is very high (Ackermann *et al.*, 2001; Chicco and Mancarella, 2009). Furthermore, each area incorporates a PEV management device called PEV manager (Galus and Andersson, 2009b; Galus *et al.*, 2012a,b). The managing entity signs the vehicles connected in its area into the scheme and performs optimizations in order to determine whether the power system is capable of supplying the additional load. Constraints on the total consumption of power by the PEVs are derived from the network state including the base load. Typically, the transformer and line capacities as well as the voltage levels in medium- and low-voltage networks limit the transmittable power at nodes, i.e., hubs. For simplicity, only the transformer and CHP capacities are considered as limiting factors.

In the PEV manager optimization scheme, a benefit function and an individual utility are assigned to the PEVs based on the battery energy level

Figure 3.2 Four-hub network including PHEV managers for urban areas.



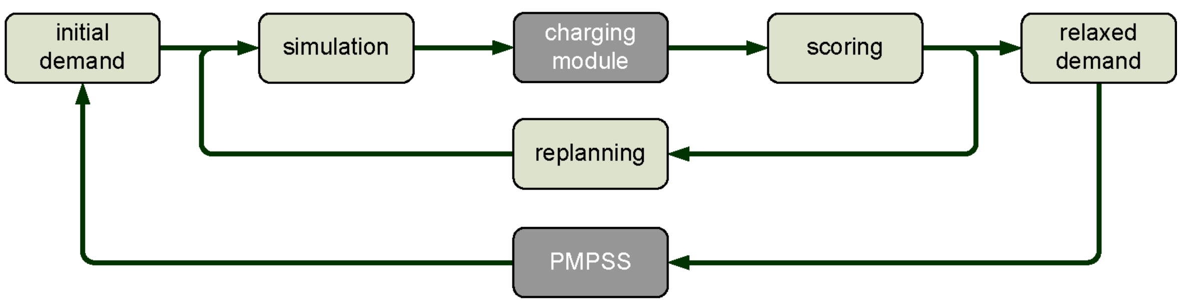
and the charging activity (Galus *et al.*, 2012a,b). The utility function depends on the relative state of charge (SOC), the desired SOC at departure, the departure time, and an exogenously given price signal. In congested networks, the PEV manager creates a control price signal which is derived from the optimization. The control price signal is directly correlated with the network state, the number of PEVs demanding power and the urgency with which they demand it. This control price signal differs from system energy prices which are used to minimize overall energy carrier consumption costs.

3.3 Methodology and Simulations

3.3.1 Overview

In order to investigate different charging strategies, MATSim and PMPSS are combined and a charging module is implemented (see Figure 3.3). The charging module receives information about vehicle movement and vehicle parking times from the MATSim micro-simulation. Based on the charging scheme which is being investigated (e.g. smart charging), it derives the energy consumption of the vehicles, which is based on a simple PEV model simulating actual driving cycles in cities (Galus and Andersson, 2009a). For the scenarios which are investigated, standard (3.5 kW, 240 V, 16 A, single-phase) Swiss plugs are assumed. The charging module knows where each vehicle is parked, and for how long. For charging, three different strategies are implemented: dumb charging, dual tariff charging and smart charging (see Sections 3.2, 3.3 and 3.4; the strategy names follow Lopes *et al.*, 2009). After assigning charging times to the cars, the charging module can assign scores to the agents (e.g., the cost of the electricity charged). Once the MATSim simulation process has reached a relaxed state, the charging times, locations and state of charge of the agents are sent to the PMPSS. The PMPSS determines whether the electricity demand based on these charging times together with the base load violates certain physical network conditions, as described in Section 3.2.2.

Figure 3.3 Charging module with PMPSS added to the MATSim simulation process.



For some applications it could be enough to know, where overloads in the electricity grid occur, while for other application (such as the one in Section 3.4), iterations between the transport simulation and the PMPSS are might be required to avoid network overload and to determine a favorable charging schedule for the vehicle fleet. In order to enable an information exchange between MATSim and PMPSS, a control price signal is sent back from PMPSS to MATSim after each iteration for the whole day. The higher the control price signal the more congested the network. If the PMPSS control price signal indicates congestion in the network, a new MATSim iteration is started. If no constraint violation occurs, the physical network can meet the PEVs' electricity demand and a viable charging pattern has been found. The initial price used by the charging module depends on the charging scenario to be simulated, e.g., dumb charging or dual tariff charging.

As MATSim simulates a 24-h day, it is assumed that the agents start in the morning with a full battery and try to fully charge it again before starting the next day.

Table 3.1 Overview of Scenarios.

Scenario	**Description**	**Figure**
Scenario A	Dumb charging scheme, PHEV	10,11
Scenario B	Time of use charging scheme, PHEV, low price from 9 p.m. to 5 a.m.	12
Scenario C	Time of use charging scheme, PHEV, low price from 3 p.m. to 5 a.m.	13
Scenario D	Time of use charging scheme, only EV – low price from 9 p.m. to 3 a.m., else excessively high	14
Scenario E	Smart charging scheme, PHEV, initial price control signal based on base load curve	16-18
Scenario F	Smart charging scheme, PHEV, bad initial price control signal	19
Scenario G	Smart charging scheme, PHEV, maximum power at hub 1 decreased to 8.5MW	20

In the following sections the different charging schemes are presented together with simulation results. Table 3.1 gives an overview on the scenarios.

3.3.2 Dumb Charging Scheme

"Dumb charging" means that agents start charging their cars as soon as they arrive somewhere, in the attempt to fully recharge the battery. The dumb charging scheme assumes that the costs of electricity are the same throughout the day, and therefore agents connect their PEVs to the energy system as soon as they arrive at a location.

For testing this charging scheme, a simplified Berlin scenario is used (Rieser *et al.*, 2007), which is available to test new MATSim models. The city of Berlin, Germany is divided into four parts, and each part is assigned a hub. Each hub incorporates a base load curve that corresponds to a typical urban area (residential, industrial or business). The maximum power input, e.g., transformer capacity ratings for hubs 1–4 is defined as 9 MW, 4.4 MW, 8 MW and 8.2 MW, respectively. The maximum usable battery capacity of each PEV is assumed to 10 kWh.

In the test scenario, only car trips with home–work–home and home–education–home activity chains are considered. It contains a 1% population subsample of Berlin with 16,000 agent plans.

In Figure 3.4, the energy consumption at the different hubs after applying dumb charging is shown (Scenario A). Hub 1 dominates in consumption, as it is assigned more transportation network links and hence activities. As expected, the energy consumption displays typical morning and evening traffic peaks. When the charging times of each agent are sent to the PMPSS, it produces price control signals for the hubs, as shown in Figure 3.5. The price control signal is measured in [Rp./kWh], where one Swiss Franc contains 100 Rappen (Rp.). A price signal of 9.0 Rp./kWh indicates no congestions, whereas peaks above 9.0 Rp./ kWh indicate violations of the maximum power capacity of the hubs. The height of the peaks correlates to the intensity of constraint violations in the energy system. Even though the peak load from the PEVs is lower in the evening than during the day, the PMPSS price signal is still higher, indicating a higher base load (e.g., household consumption of electricity) in the evening hours.

Figure 3.4 Vehicle energy consumption with the dumb charging scheme.

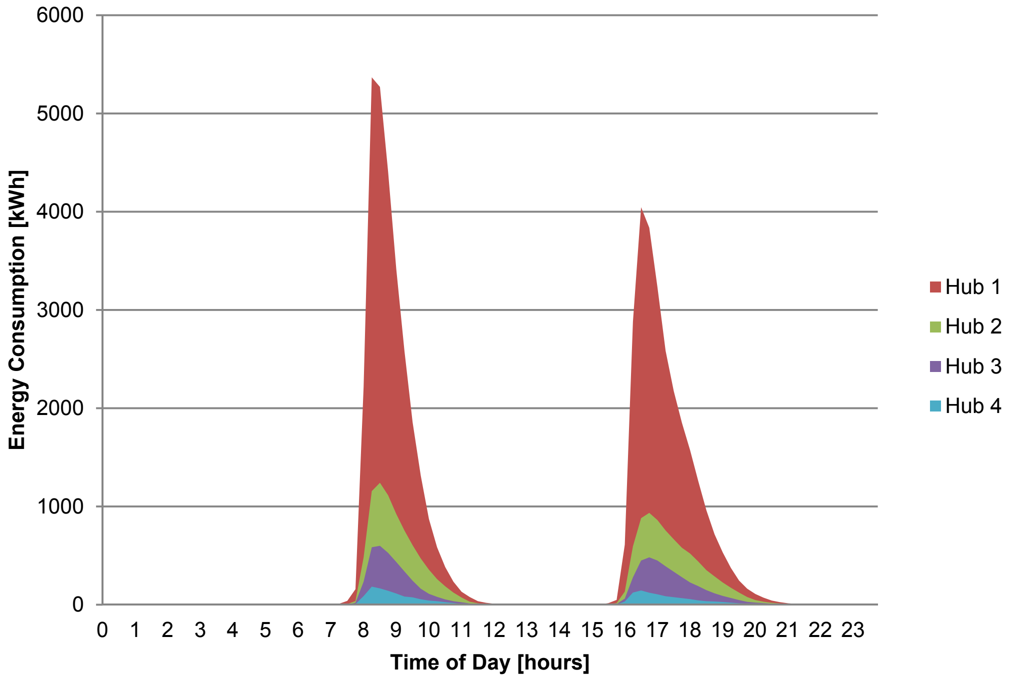
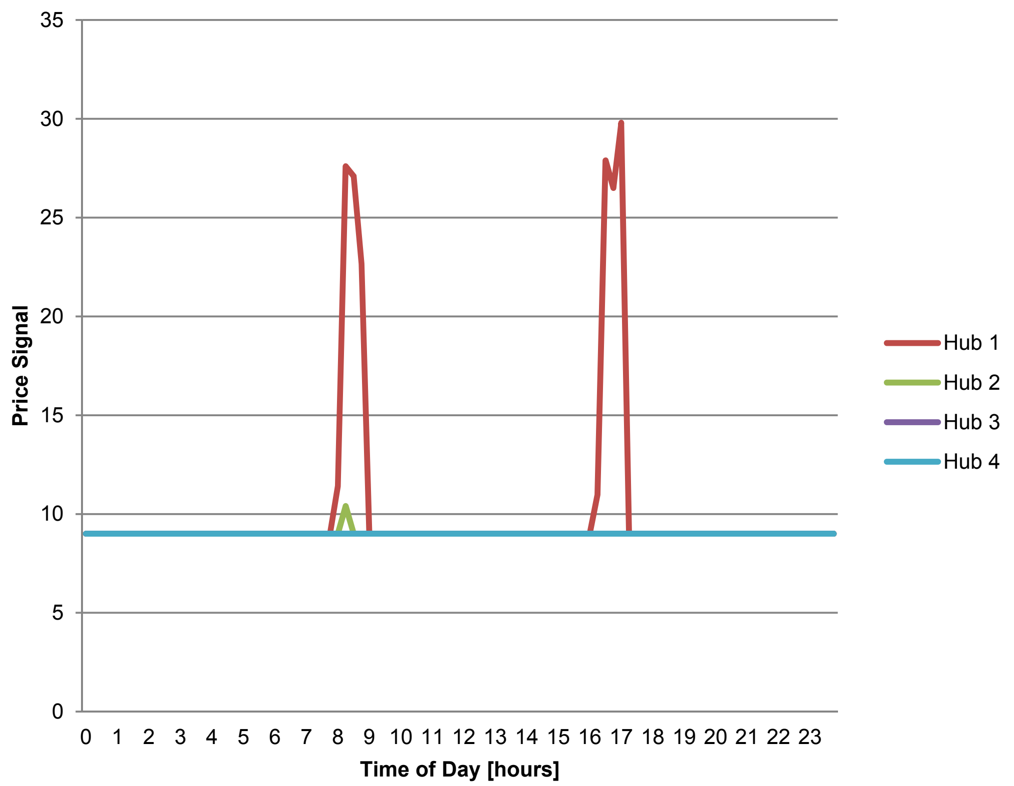


Figure 3.5 PMPSS price signal for dumb charging.

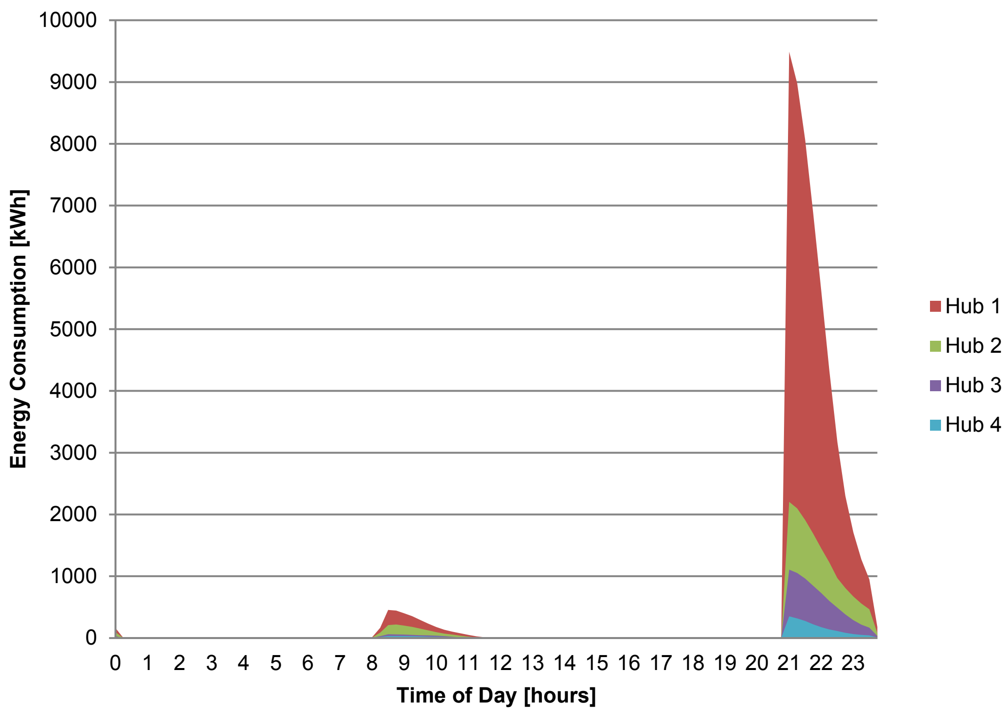


3.3.3 Dual Tariff Charging Scheme

One approach which is used by many utilities today in order to shift load is a dual tariff strategy, also known as "time of use" (TOU) pricing. Electricity consumption is much lower at night than during the day. In order to give people an incentive to shift their consumption (use of washing machines, etc.) to later times, i.e., off-peak hours, the price of electricity is low during the night (e.g., from 9 p.m. to 5 a.m.) and high throughout the rest of the day.

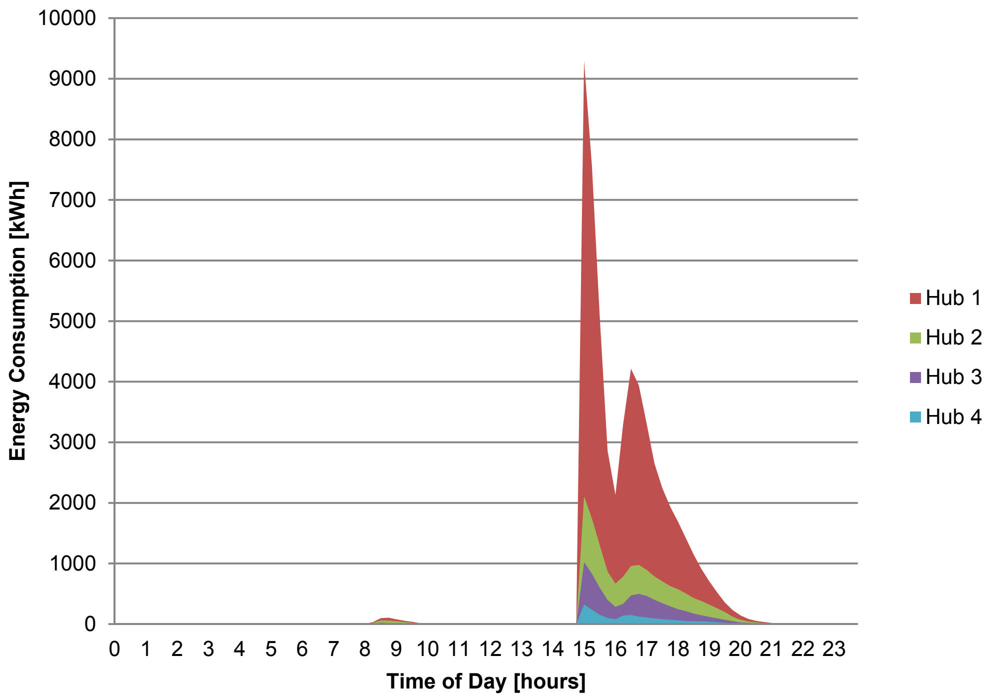
To model such a scenario (Scenario B), the price for electricity is set to 9 Rp./kWh from 9 p.m. to 5 a.m. and to 18 Rp./kWh for the rest of the day. The agents are expected to charge their vehicles with just enough energy to get back home (during high tariff times) and fully charge their PEVs at night after the low tariff pricing starts. The resulting pattern, simulated with the implemented charging module, is depicted in Figure 3.6.

Figure 3.6 Vehicle energy consumption with a dual tariff charging scheme (low tariff from 9 p.m. to 5 a.m.).



Agents who need energy to return home start charging their vehicles immediately upon arrival at work. The agents stop charging when a sufficient amount of energy is attained to reach their home location. At 9 p.m. all agents who are at home start to charge their vehicles. The peak generated in this charging scheme is almost twice as high as the one generated by dumb charging, as it contains both the morning and evening energy demand, previously observed in the dumb charging scheme. Since most agents arrive home before 9 p.m., the load peak perceptibly shifts to hours after 9 p.m. This leads to high energy system loads, resulting in high PMPSS control price peaks with maximum heights of 41.79 Rp./kWh for hub 1 and 41.93 Rp./kWh for hub 2.

Figure 3.7 Vehicle energy consumption with a dual tariff charging scheme (low tariff from 3 p.m. to 5 a.m.).

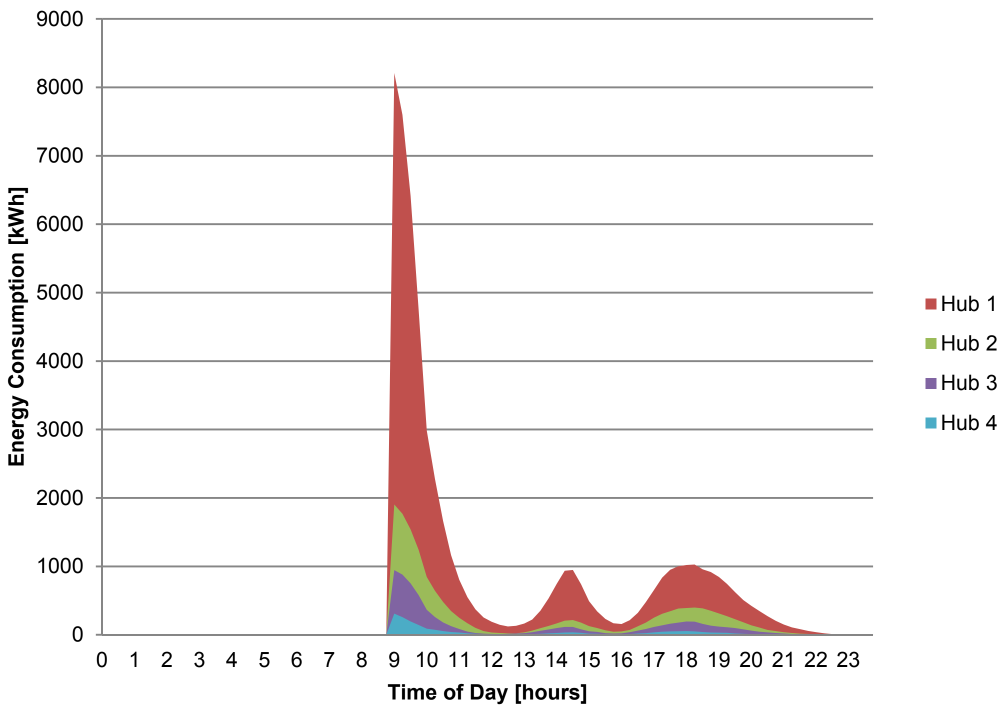


It could be argued that the low tariff starting time is set late, and that starting the low tariff period earlier could reduce the intensity of the peak. In a “best-case scenario” (Scenario C), the start of the low tariff could be set to begin before 3 p.m., when people first begin to arrive home, as can be concluded from Figure 3.4. Indeed, this approach would help to distribute the load better than in the previous scenario, but the load peak at 3 p.m. would still reach a similar height (see Figure 3.7). In fact, it would increase a bit, because vehicle charging in the morning would decrease as agents who are still at work at 3 p.m. and need energy to return home would start charging at 3 p.m. instead of in the morning. In addition, the load peak would be shifted to times where the systems electric load is high already. Hence, such an extreme case would further aggravate the system stress, i.e., high loads, instead of resolving the problem.

Note that in these two dual tariff scenarios, the price of electricity is comparatively cheap to the achievable utility of performing activities, e.g. earning money. Therefore the price does not motivate agents much to change their travel behavior, e.g. their arrival and departure times for activities.

The next example shows that the travel behavior of agents can be changed by increasing the charging price strongly (see Figure 3.8). Such an extreme scenario (Scenario D) is merely meant to demonstrate how the price of electricity, integrated in the utility function of MATSim, influences agent travel behavior. For this experiment, agents, who can complete their trips using electricity only, are assigned EVs.

Figure 3.8 Vehicle energy consumption with a dual tariff charging scheme (low tariff from 9 a.m. to 3 p.m.).



Excessively high charging tariff during the rest of the day.

Agents with longer trips between activities (who could not complete their travels using EVs), are assigned conventional vehicles and as such are not part of the analysis. As EVs are assigned to agents instead of PHEVs, the

EV owners have not the option to switch to gasoline if the electricity price rises above the gasoline price level. Additionally in this scenario agents are not allowed to switch the transportation mode or vehicle type. For this experiment, the low tariff is set between 9 a.m. and 3 p.m. During the rest of the day, the price of electricity is set to a very high value (much higher than the agents can earn through working – corresponding to infinity). Hence, it is vital for the overall utility score of the agents that they charge their vehicles between 9 a.m. and 3 p.m. As the agents in the simulation are not allowed to drop any activities, they leave to work earlier in the morning and come back home immediately. By doing so, the agents can charge their cars for the next day taking advantage of the low electricity prices. The simulation result shown in Figure 3.8 is derived from a still-evolving MATSim run; therefore, some agents still charge their vehicles after 3 p.m.

Based on Scenarios B and C, it seems obvious that a pricing scheme which is more granular than the dual tariff pricing scheme could be an alternative, e.g., with 1 h intervals. In such a case, manually connecting and disconnecting the PEVs seems impractical. Instead, an approach that utilizes ICT in both, the vehicles and the energy system, seems more appropriate in order to handle this problem. In the next section a solution is implemented which takes the electric load and network constraints into account and is active in 15-min time steps. The 15-min interval is used because it is the current measuring and accounting interval for electricity in power networks.

3.3.4 Smart Charging Scheme

There are many ways to implement smart charging. One way is to give more control to the utilities that own the electricity grid. The utilities could receive information from car owners, such as where and how long their vehicles will remain parked and their expected energy consumption for the rest of the day. Based on this information, a central utility controller could determine for the PEVs when and when not to charge. In a V2G scenario, the controller could also determine when to feed power back to the energy system. Appropriate electricity rates could be based on a contract between the utilities and PEV owners, whereby the owners of vehicles, which stay connected to the energy system for a previously announced duration would receive cheaper rates. Longer connection to the energy system could also result in lower electricity prices for the PEV owners, as the PEVs could be used as storage for buffering electricity. Such an approach in which a central entity possesses network, load and generation information and is able to decide when the PEVs are to be charged or discharged is hereafter referred to as *centralized smart charging.*

A second way to implement smart charging would be to publish a charging and discharging rate scale based on time and locality. Software in the PEVs could then decide when to charge or discharge electricity. An algorithm used to make such decisions would depend on data, similar to that needed in the previous case: parking duration and the location of the next activity. Here, the approach in which a PEV (and its owner) can decide when or when not to charge the battery is referred to as *decentralized smart charging.*

Whether one of these two general approaches or even a mixture of the two will become established depends on many factors, including legislation, utility policy, car manufacturing and smart grid evolution. It is unclear which approach would lead to a more robust grid infrastructure, an important goal of the smart grid initiative. Here the first approach will be presented. One possible application of the second approach has been implemented in PMPSS (Galus and Andersson, 2009a), but it may become necessary for it to be reimplemented in the charging module in order to meet the energy demand of agents' longer activity chains.

Centralized Smart Charging Scheme

In the centralized smart charging model, which has been implemented and tested as part of the current work, a PEV's onboard computer tells the smart grid what trips are planned for the day together with the car's location and the expected duration of the activities throughout the whole day. Although it can be assumed that people are able to make rough estimates of their weekday activities, smaller variations in working times can still happen in real life (see Section 3.4.3 for further discussion and future work).

To give an example, an agent not only tells the smart grid that he or she will go shopping after work, but also that the agent will drive home directly from shopping. The current policy is set in such a way that the smart charging model ensures that all cars are fully charged by morning in time to start the next day. Providing the central smart entity information on the next trip, e.g. shopping, and on the subsequent trip (driving home) gives the smart charging algorithm a wide range of flexibility. The smart entity can decide when and when not to charge a PEV depending on the electric load while trying to fulfill the constraint that all PEVs should be provided with enough energy, so that they can drive home using electricity only (if possible). Such agent cooperation could be rewarded by the power utilities, e.g., by offering them a lower price per unit of electricity.

The MATSim–PMPSS iteration starts with the above-mentioned vehicle activity information and assumptions about the initial base load. If no initial base load information at a location is given, a constant base load is assumed. Then the smart charging is performed based on the vehicle's energy demand constraints. After each MATSim–PMPSS iteration, the smart charging algorithm determines whether the proposed charging scheme was successful, i.e., the feedback from the PMPSS does not reveal control price signal peaks. Should this not be the case the algorithm tries to reschedule charging times so that energy system constraint violations are avoided.

Simulations

In the first smart charging simulation (Scenario E), the price at the start of the smart charging scheme is based on a control signal directly proportional to the actual base load of each hub. Five combined MATSim–PMPSS iterations are needed before a charging pattern, which does not cause constraint violations of the energy system is found. The vehicles' consumption of electricity in the first iteration of the experiment is shown in Figure 3.9. Even though the charging activity of vehicles is lowest in the evening for hub 1, several price signal peaks occur (see Figure 3.10). The vehicles' consumption of electricity after the fifth iteration (Figure 3.11) does not exhibit any price signal peaks. As expected, the smart charging scheme produces vehicle electricity consumption levels which are much lower than the ones observed for dumb charging or dual tariff charging. Figure 3.12 shows the price signal peak intensities for the first four iterations at hub 1. The number of physical energy system constraint violations are lower in the third and fourth iteration than in the first two iterations, as expected.

Figure 3.9 Smart grid experiments: The PEV electricity demand after the first MATSim-PMPSS iteration. Real base load formation available to the charging module.

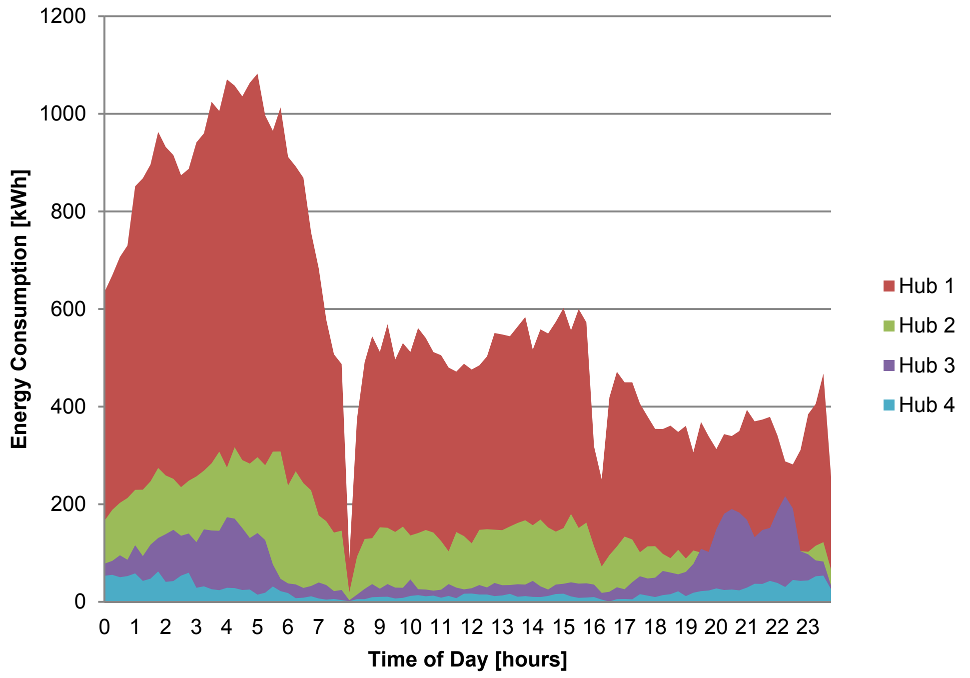


Figure 3.10 Smart grid experiments: The PMPSS price signals based on the electricity demand in iteration 1.

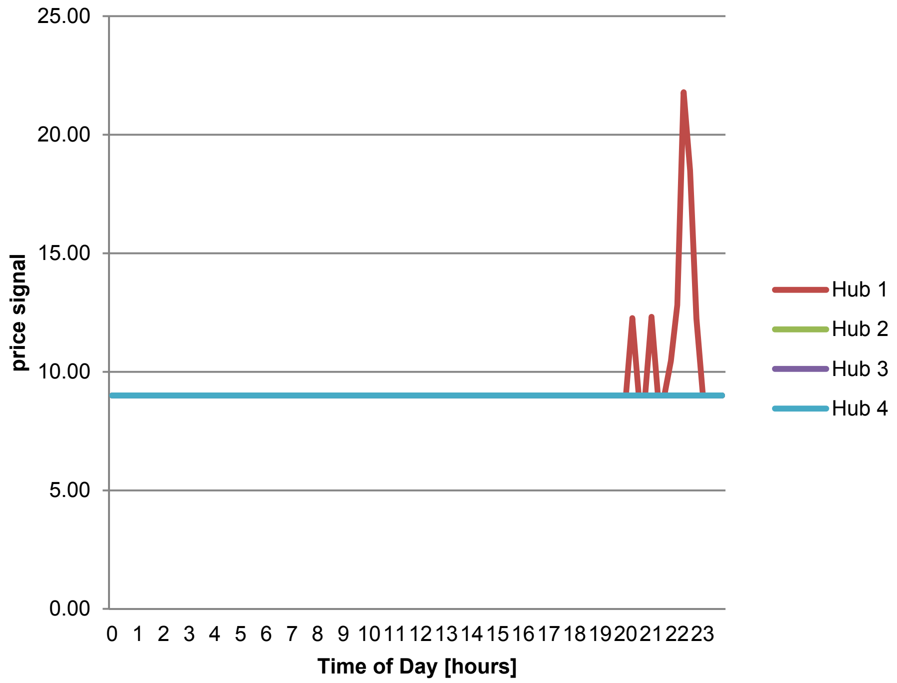


Figure 3.11 Smart grid experiments: Electricity demand by the PEVs in iteration 5 does not cause any peak price signals.

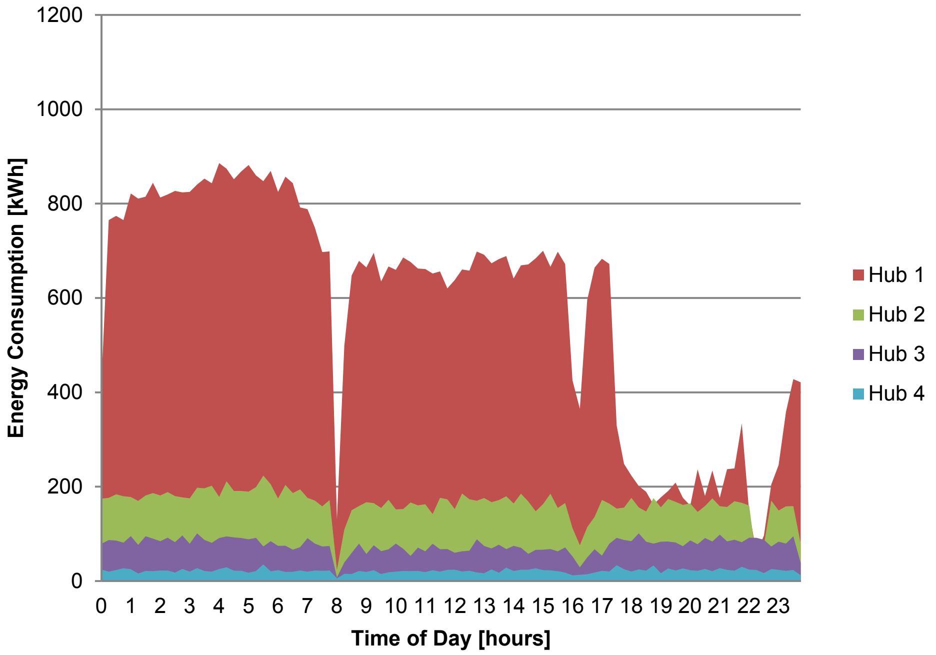
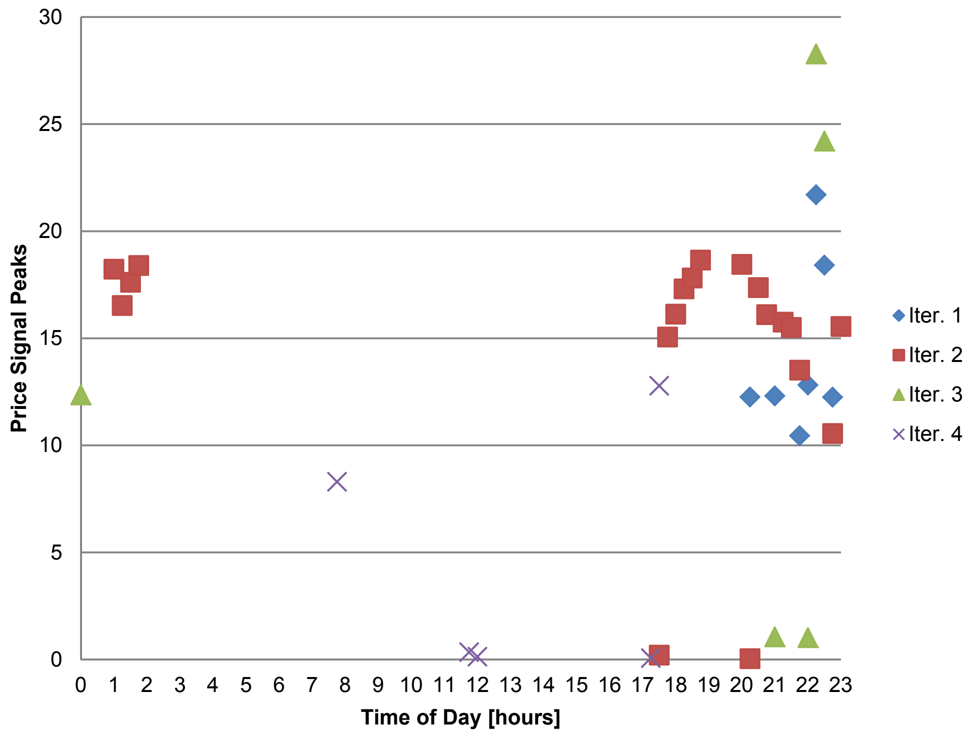
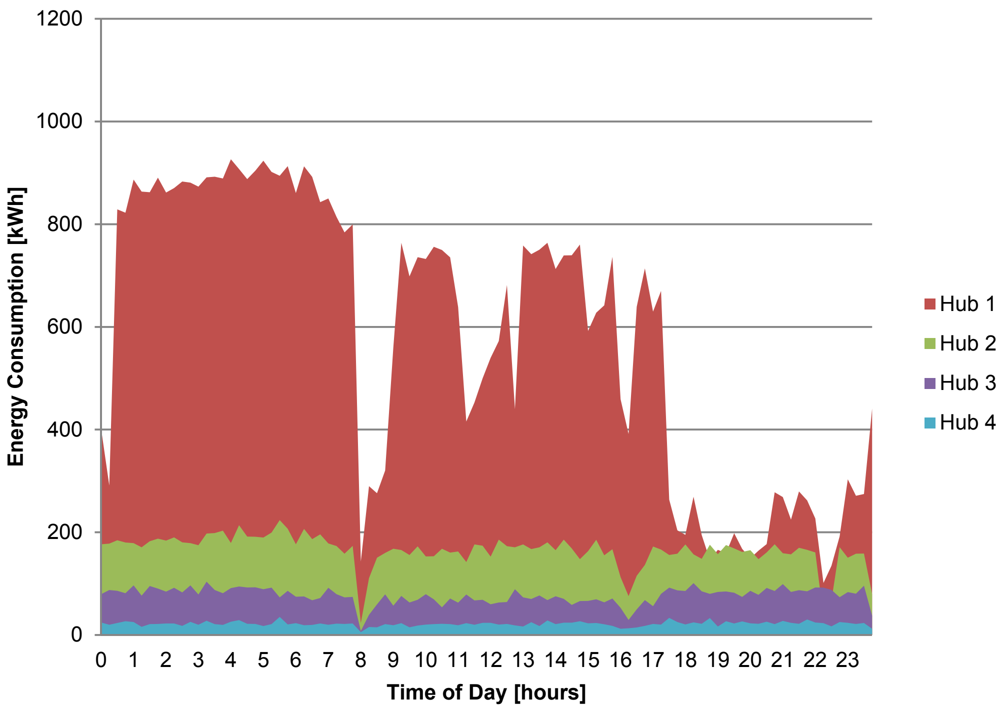


Figure 3.12 Smart grid experiments: The PMPSS price signal peaks for the first four iterations at hub 1.



In contrast to the first simulation (Scenario E), in which the price at the start of the charging scheme is based on the actual base load of each hub, a second experiment is performed (Scenario F) in which wrong information about the base load is given to the charging module to demonstrate that the smart charging scheme can find a solution independent of the initial load information. The initial control signal is set very low from 9 a.m. to 3 p.m. and high for the rest of the day for all hubs. The smart charging algorithm found a solution which does not cause any constraint violations after seven iterations. Figure 3.13 shows the vehicles' electricity consumption after the final charging in the seventh iteration. The results are similar to the charging behavior found in Figure 3.11. Even though it takes two iterations more than the previous simulation which uses an initial control signal based on the actual base load, this experiment demonstrates that the smart charging algorithm is able to find a solution independent of the quality of the initial control signal (although it may require additional iterations). Thus it is robust.

Figure 3.13 Smart grid experiments: Experiment using a bad base load assumption.

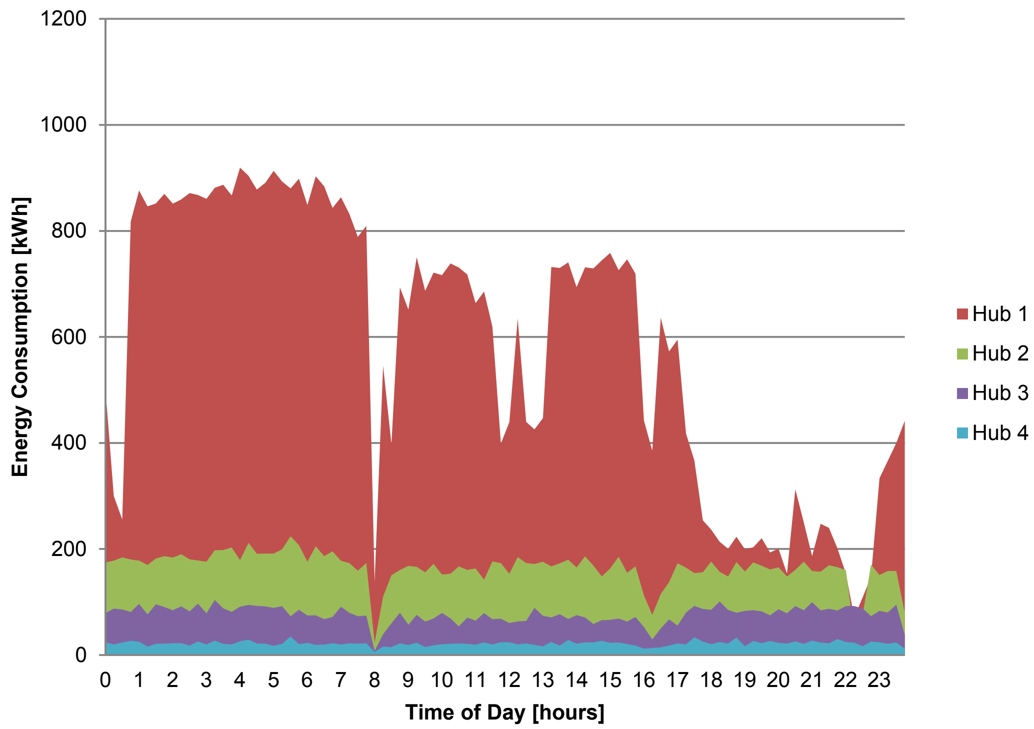


A charging pattern which does not result in any peak price signals is found after seven iterations.

Up to this point the maximum power input for hub 1 is 9 MW. When the maximum power of hub 1 is decreased to 8.5MW (Scenario G), the smart charging scheme finds a solution after 15 iterations even under these tight energy system conditions (see Figure 3.14). This solution is similar to Figure 3.13 as only minor electricity consumption peaks needed to be reduced in order to find a charging pattern which does not violate any energy system constraints. When the value is decreased further to 8 MW, the system does not relax, even after 25 iterations. This is because the capacity of the physical energy system is no longer able to accommodate all vehicles.

One point, which is observed in all smart charging scenarios, is that the electricity demand declines at around 8 a.m. and 4 p.m. This occurs, because around these times most agents in the simulation test scenario are traveling by car and hence they cannot charge.

Figure 3.14 Smart grid experiments: The maximum input power of hub 1 is reduced by 0.5 MW compared to all previous experiments.



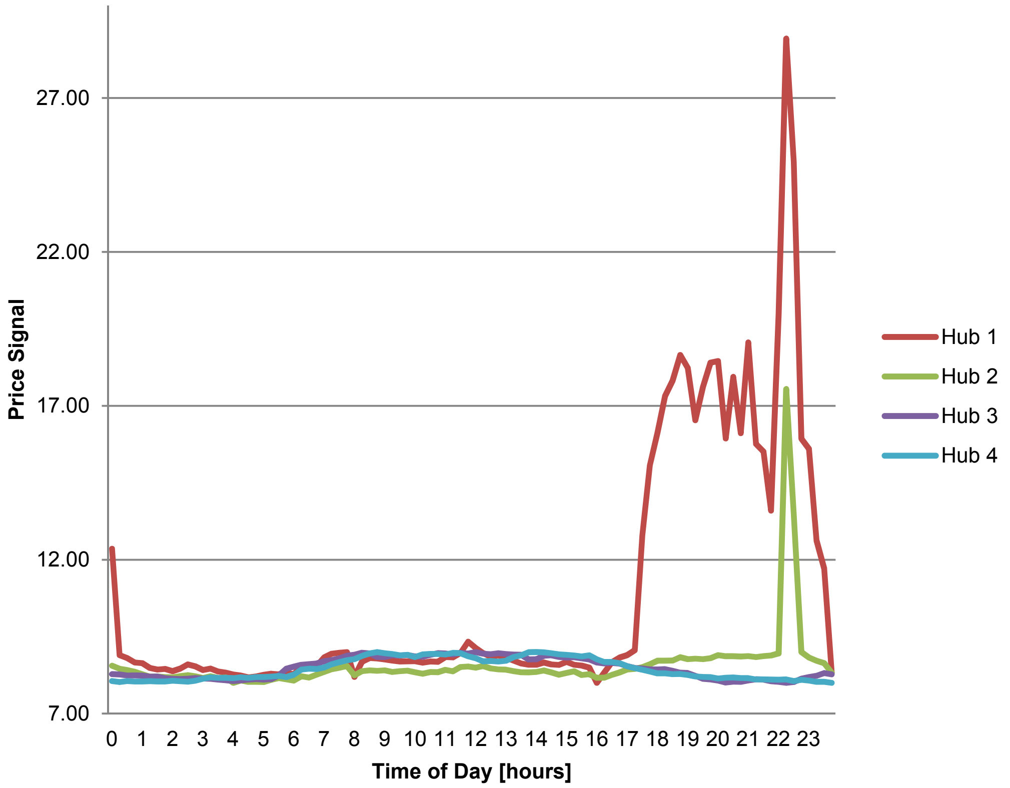
It took three times as many iterations compared to the original experiment to find a charging configuration which did not cause any network violations.

How can the System Relax?

The smart charging algorithm uses the PMPSS as a black box to receive information about energy system load for a certain charging pattern. The system could never relax if only the control signal from the PMPSS is considered by the smart charging algorithm. If the charging module produces a charging pattern which does not violate any constraints, the PMPSS just gives back a constant price signal of 9.0 Rp./kWh. If the charging module receives only such input, it is as if the PMPSS sent no information, and the system could again produce peaks.

Therefore to achieve system relaxation, the smart charging algorithm learns about system constraints over the iterations. This is done by keeping an internal price signal in the charging module. This price signal is based on MATSim–PMPSS iterations. For example, if there is a constraint violation from 6:15 a.m. to 6:30 a.m., the charging module will remember its intensity. In the next MATSim–PMPSS iteration the charging module will adapt the charging pattern, and fewer vehicles will charge between 6:15 a.m. and 6:30 a.m.

Figure 3.15 The internal price signal of the charging module after the 5th iteration of the first smart grid experiment.



The internal price signal of the smart charging module from Scenario E just after the 5th iteration is shown in Figure 3.15. At this stage the control signal received from the PMPSS does not show any peaks, as no energy system constraint violations appear. This internal price signal of the charging module contains information learned about the base load, the vehicles' energy consumption, and also at which PMPSS price signal level constraints violations could occur. Utilizing this information, the charging module achieved a relaxation of the system and load balancing.

3.4 Discussion and Future Work

3.4.1 Vehicle-To-Grid Technology

Although the simulation system and output presented here can help to make rough estimates about the potential of V2G technology in case of power system emergencies, the presented smart charging module still lacks the ability to simulate discharging. Furthermore, a future energy system should be able to cope with distributed energy generation (National Energy Technology Laboratory, 2007). Whether energy is generated from a solar roof on top of a house or is excess energy from the solar roof of an EV, it should be possible to feed it back into the energy system. Whereas energy is traditionally transported by power lines, energy in a V2G-enabled smart grid could be charged in one area of the network, transported via PEVs and fed back at a different spot. For example, a person could charge his car from his solar panel and discharge some of the energy at a nearby shop with a parking lot equipped with electric dis/charging stations. In this case also battery limitations need to be considered. The MATSim–PMPSS framework presented here provides a solid basis for analyzing the dynamics of future smart grids in terms of time and space especially in connection with PEVs.

3.4.2 Designing the System

The charging module presented within the MATSim–PMPSS iterations can be used to investigate how electricity networks need to be designed in order to supply an additional PEV load. For example some city areas will not have the capacity to support PEV charging. Applying a smart charging algorithm could help: PEVs from such areas could be charged during the day at other locations, e.g., the workplace could become their primary charging place.

3.4.3 Unexpected Demand

It seems reasonable that people with the ability to predict and adhere to their daily plans should be rewarded. To define a fair price for this ability, it is important to find out how much uncertainty the system could handle. Because this, amongst other factors, determines how many underutilized reserve power plants are required in the system. For example, can the smart charging algorithm handle situations in which people's plans change slightly by an order of 15–30 min at random? In a further example, if 5% of the car users departed from their original activity plan during the day, for instance to engage in sports instead of working, how would this impact the energy system, i.e., the electricity grid? How does the energy system behave when little data about people's activities is available (e.g., only information about the next activity of the day)?

The algorithms, which are used in the charging module for smart charging could also be applied to decentralized smart charging in the real world. At the moment, the smart charging module is not tuned towards handling unexpected demands for electricity. If the demand changes during the day, the smart charging algorithm can be run again to adapt to the change.

3.4.4 Simulating Heterogeneous Vehicle Fleets

In this chapter, only the energy consumption of PEVs is tracked. In future research this should change. At the moment, data about the energy consumption of a whole range of vehicle types is being prepared for Switzerland. The data produced will depend on maximum speed limits, average speeds driven and vehicle engine types. This will allow simulating both the energy consumption and the greenhouse gas emissions of the vehicle fleet in Switzerland much more precisely than with the model utilized here.

3.4.5 Utility of Agents

In this chapter MATSim runs are used to generate a relaxed traffic demand for the charging module. In Scenario D it is shown that excessively increasing the price of electricity could induce electric vehicle users to change their travel behavior and drive to work earlier. In the future, agents should have more alternatives, e.g. if an agent using an EV is unable to reach his or her destination because it runs out of electricity, the agent might change to a different vehicle type or transportation mode (if no electric fuelling stations are introduced). Conversely, when gasoline prices are high, people might want to switch to PEVs. This would require good estimates of the utility parameters, which could for example be obtained from a stated preference survey (see for example Jäggi and Axhausen, 2011; Erath and Axhausen, 2009).

3.5 Conclusions

Previously, aggregated traffic models have been used to model PEV electricity demand. Such models are appropriate to uncover grid wide electricity demand peaks, but are unable to pinpoint bottlenecks in the electrical network at various voltage levels, as these require high resolution spatial information. To the best of the authors' knowledge, the approach presented is one of the first attempts to successfully use a micro-simulation to overcome this obstacle to model potential electricity demand by PEVs. It is demonstrated that with the framework presented a variety of PEV charging policies can be tested. It is found, that although dual tariff charging schemes are effective in changing user behavior, their application in a real-life PEV context might cause more harm than good to the electricity grid depending on the scenario, e.g. base load and maximum transformer output. Through experiments it is demonstrated, that such problems can be overcome by smarter charging schemes, where communication technology between vehicles and the grid is involved.

The presented approach allows utility owners to analyze electric grids in order to determine whether the network capacity is sufficient for a particular penetration of PEVs. Several research topics surrounding this chapter are in progress: At the time of writing (2009), the presented approach is being applied on a real-live scenario to the city of Zurich, Switzerland and its surroundings containing more than one million vehicles. Even though this chapter already allows investigation of a variety of smart charging schemes, it also opens ways to new research: One question is how could decentralized smart charging work and if that is a viable solution. Furthermore, it is planned that the presented framework should be extended by adding the possibility of speed-charging stations, which allow fast charging of PEVs. This would help both to optimally plan such infrastructure and to investigate its impact on traffic demand and the electric grid.

Chapter 4

An Agent-based Parking Choice Model

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4.1 Introduction and Background

Car owners often enjoy higher travel time flexibility and shorter trip durations than public transit travelers. But this flexibility comes at a high cost in terms of infrastructure including parking (Shoup, 2005). Public authorities are often responsible for investing in such infrastructure. Therefore, they play an important role in shaping travel demand by introducing new policies, such as changes in parking price or capacity. In order to help such authorities make informed decisions, travel demand simulation models are used. However, these models, especially large-scale ones, often lack a model for parking (MATSim, 2011).

There is vast literature discussing the different aspects of parking and parking policies. Willson and Shoup (1990), for instance, found that employer-paid parking increases solo vehicle drives to work. Huber (1962) reported that parking search related traffic can amount up to 20% of the total traffic at the city center. Axhausen and Polak (1991) tried to deconstruct the parking search into its various components: general in vehicle time, parking search time, walking time, parking cost, etc. and valuation of these components. Axhausen (1989), describes search strategies often followed by the drivers. Hess and Polak (2004) further suggest that there is a significant variance in personal preferences when it comes to the valuation of the different components of parking related time. One group of people might value search time much higher than others, for example, while another group might put more importance on walking time.

In Polak and Axhausen (1990) an early and extensive discussion of this topic can be found, where the need for better and practical methods for modeling parking search behavior is stressed. In order to model the individual behavior of people with potentially different preferences, *agent-based* models seem suitable, where — instead of looking at aggregated traffic flows along roads — individual people/drivers called “agents” are simulated and tracked (MATSim, 2011). At the moment only a few agent-based simulation models for parking exist that which could potentially take individual preferences into account (Benenson *et al.*, 2008; Spitaels *et al.*, 2009). Both these agent-based models have been successfully applied in parts of different cities containing less than 100,000 agents.

The current chapter proposes a new model for parking, which focuses on parking choice and uses an agent-based model to capture individual valuation of time and differences in taste. One of the main challenges with agent-based models is finding the right level of abstraction, so that larger scenarios are also computationally feasible. The proposed parking choice algorithm has been implemented into an existing travel demand simulation framework, which is aimed at the simulation of large-scale scenarios with millions of agents (MATSim, 2011). In the next section, this parking choice model is presented and is followed by a description of the implementation of the model and the simulation results.

4.2 The Parking Choice Model

As mentioned in the introduction the focus of the chapter is parking choice. In this context, we define *parking choice* as the decision-making process of selecting a parking space from a given set of parking spaces located close to the agent's destination. In the model presented, we intentionally leave out the parking search process to simplify our model. Therefore, our model is aimed at static decision-making rather than at the decision-making of an agent travelling along a link in a traffic simulation. We envision that the current model will be extended and adapted to accommodate parking search in the future. For the same reason the model is limited to parking choices encountered in everyday life where the agents already are somewhat familiar with the parking situation at the destination.

4.2.1 Parking Types

It is often observed that four types of parking scenarios exist, which we model as distinct parking types. The following parking types are part of the current parking model:

- Public parking: Parking that is not reserved for any one. All agents can compete for these parking spaces.
- Private parking: These parking spaces are assigned to specific activities and buildings. E.g., parking at home or at a shop that can only be used by residents or shoppers.
- Reserved parking: Parking reserved for a selected set of agents. E.g., parking reserved for disabled people.
- Preferred parking: Sometimes it is necessary that for a car to park at a location with a certain characteristic. E.g., a person driving an electric vehicle might require a parking space with a power outlet for charging.

The first three parking types depend on the static properties of parking while the fourth parking type is more abstract and dynamic, as it encompasses the individual situation and the preferences of drivers, combined with the properties of the parking itself. Therefore, the same parking could qualify as preferred parking type for one agent but not for another.

4.2.2 Utility Function

Assume a person is given a choice set with two spaces to select from. In this case, there are several parking attributes, which the person can consider. Furthermore, two different people might prefer different spaces from the same choice set, depending on socio demographics like age, gender, or income. In our model, we assign a utility score to each parking space from a simulation agent's perspective to compare different parking spaces. Such a utility score might look like Equation (4.1).

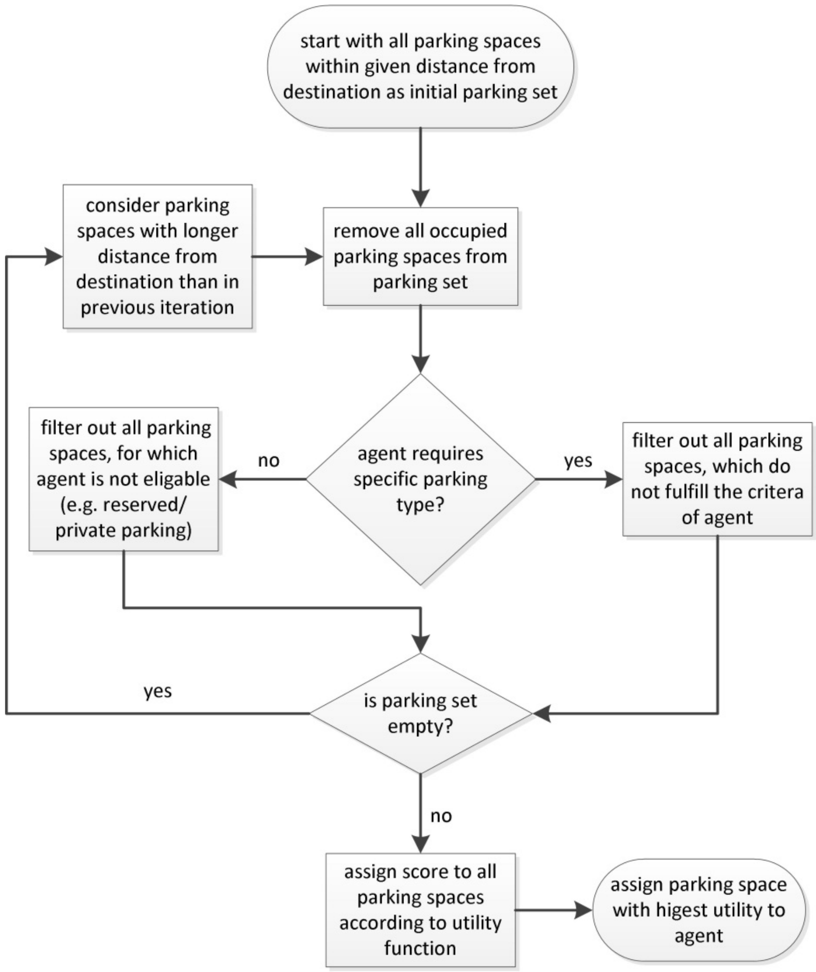
$$U_{parking} = \sum U_{walking} + U_{parkingCost} + \cdots \quad (4.1)$$

The walking distances to the destination or the parking cost are both characteristics that have an influence on peoples' decisions and are, as such, part of the utility function. Parking cost can further depend on parking duration and time of day. And, of course, income has an influence on how strong the parking cost is perceived. More factors can be added to this utility function, such as security concerns, where the same parking space could be perceived according to gender and time of day. Of course the different parts of the utility function have to be properly weighted according to the valuation of the person, which can stem from stated/revealed preference choice surveys, (see, Erath and Axhausen, 2009).

4.2.3 The Parking Choice Algorithm

For each parking choice decision for a given destination, the algorithm depicted in Figure 4.1 is applied. The algorithm starts with all parking spaces located close to a destination. From this set of spaces first all occupied spaces are removed. Then, if the agent is looking for a certain type of parking (*preferred parking*), all spaces not fulfilling those criteria are discarded from the set. If the person is not looking for *preferred parking*, spaces that the person is not eligible for are filtered out (e.g., reserved parking or private parking). If the set resulting after the execution of this filtering process is empty, the algorithm begins again with a larger radius, extending the distance from the destination. If the set contains some parking spaces, a utility score is calculated for each parking space, according to the utility function described in Equation (4.1), and the parking space with the highest utility score is assigned to the agent. After this assignment, the parking space is marked as occupied by the agent and is no longer available for other agents.

Figure 4.1 Parking Choice Algorithm



The presented model is hierarchical in the sense that it makes decisions on two levels: On the top level, the general set of parking spaces is defined based on the parking supply (parking occupancy, reserved/private parking available and agent's preferences). Then, after the decision on the top level has been made, the individual valuation of the agent for the different properties of the parking space, e.g., price or walking distance, is considered using the utility function.

It is important that the initial parking set is large enough, for a tradeoff to be made by the agent based on the utility function. For example, if the set chosen is too small and only costly parking spaces are located close to the destination, the agent would not be able to make a tradeoff regarding walking distance and would be unable to consider parking spaces further away. On the other hand, if the parking set chosen is too large, and in the extreme case all parking spaces in the study area are selected, this would result in a performance issue.

4.2.4 External Feedback

Although the utility score presented in Equation (4.1) is only used inside the parking choice algorithm, it can also be made available to the travel demand simulation framework surrounding the parking choice algorithm. This would present the overall simulation framework with the possibility of reacting according to such a feedback from parking choice. E.g., if in an area parking supply is lower than demand, some people might have to walk long distances between their parking space and their destination. If the utility score information for each selected parking space by an agent is input to the traffic simulation, it can take appropriate steps to react the situation, e.g., by allowing the agent to change travel time, location, or mode.

4.2.5 Leaving out Decisions made at Road Intersections

As stated earlier, the model does not consider parking search. It seems parking choice decisions are a combination of acquired knowledge of the parking situation over time (Pinto and Baddeley, 1991) and decisions made while driving along roads and intersections when searching for a parking space (and, thereby, taking the actual traffic flows and occupancy of parking into account). The parking choice algorithm presented performs a partial combination of both approaches when it evaluates parking spaces according to the agent's utility function and the actual parking occupancies encountered in the simulation. In this way, the proposed algorithm always finds the best suitable parking for the agent for the given destination. Although in reality people might not always make such optimal decisions, the simulation runs shown in this chapter suggest that the model is able to capture a significant portion of elements relevant to parking choice.

In the next two sections, we describe how this simple model can be incorporated into an existing traffic simulation and applied to a larger scenario.

4.3 Implementation

In order to test our parking model, we have extended MATSim (MATSim, 2011), which is an agent-based traffic simulation framework aimed at large-scale simulations, containing up to several million agents on high resolution networks (Meister *et al.*, 2010; Waraich *et al.*, 2009a).

Figure 4.2 Co-evolutionary simulation process of MATSim

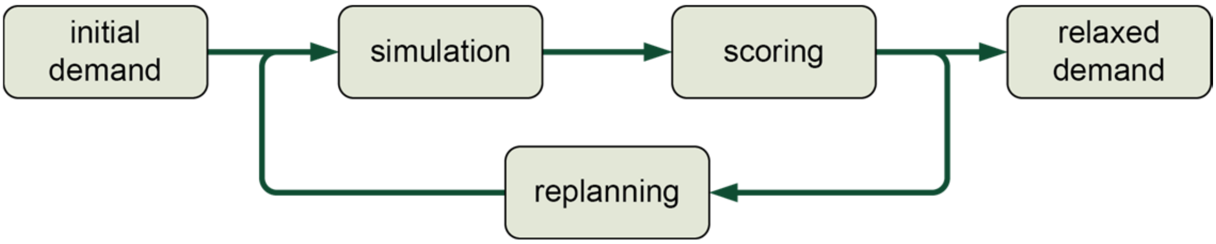


Figure 4.2 shows the MATSim simulation process: Each agent in MATSim has a daily plan of trips and activities, such as going to work, school, or shopping. The initial daily plans of the agents are provided in the initial demand, together with supply models, e.g. the street network and building facilities. The plans of all agents are executed by a micro-simulation, resulting in traffic flow along network links, which can cause traffic congestion. The execution of these plans is then scored and assigned a utility. For example, a person with a lower travel time has a higher utility than a person with a longer travel time because of traffic congestion. Furthermore working (earning money) and other activities increase the utility. The goal of each agent is to maximize the utility of his or her daily plan by replanning its day. The approached used in this context is is based on a co-evolutionary algorithm (Ciari and Axhausen, 2011). The daily plans are evaluated, and “bad” daily plans (plans with low performance, respectively low utility) are deleted. This corresponds to survival of the fittest in co-evolutionary algorithms. Thereafter, new plans are generated based on the previous set of plans. The replanning algorithm can use several degrees of freedom, such as changing routes, working time, travel mode, or location choice of agents. The execution of all plans along with their scoring and replanning, is called an iteration. The simulation is an iterative process, which approaches a point of rest corresponding to user equilibrium, called *relaxed demand*. More details about the conceptual framework and the optimization process of the MATSim toolkit can be found in MATSim, 2011.

Until now, MATSim contains a too simplistic parking model. It assumes that agents drive directly to each activity location and find a parking space there without delay. There are no constraints regarding parking supply and no notion of parking cost. The following section describes how the presented model has been integrated into the evolutionary algorithm of

MATSim, so that parking availability, price, and other factors can have an influence on the overall decision making of the agent.

4.3.1 Utility Function

As mentioned in the last section, parking choice utility can be used to give feedback to the traffic simulation. The utility function in MATSim looks like Equation (4.2), which has been extended by adding the utility term for parking as shown in Equation (4.1).

$$U_{plan} = \sum U_{travelTime} + U_{travelCost} + U_{performActivity} \cdots + \sum \boldsymbol{U_{parking}} \quad (4.2)$$

The utility score function of walking to/from parking, which is an important part of the overall parking utility, is defined in Equation (4.3). If the walking distance x between the parking and the destination becomes longer than a threshold ϑ, the marginal disutility will increase, resulting in the parking becoming increasingly uninteresting for an agent. Such a distinction is proposed, as utilities for longer distances than ϑ should be seen as a non-desirable walking distances and this information should signal to the evolutionary algorithm in MATSim that something is probably suboptimal with the given plan, and the plan should preferably be changed. The utility function in Equation (4.3) could be adapted at a later stage to incorporate individual preference data, e.g. different α and ϑ values for young and aged people.

$$U_{walking}(x) = \begin{cases} \alpha \cdot x, & x < \vartheta \\ \alpha \cdot x + \beta \cdot (x - \vartheta), & x \geq \vartheta \end{cases} \quad (4.3)$$

$$\textit{with } \alpha, \beta < 0; \alpha \gg \beta$$

The utility for parking cost has been modeled simply for the moment with a linear relationship with income. It is calculated as the parking cost (adjusted to the utility of performing activities) divided by the income of the agent. As in the simulated scenario in the next section, the income for the agents is not known, this simple utility function for parking cost seems adequate for the moment. But this will be altered to consider non-linear effects in the valuation of parking cost with respect to agent's income for the given scenario (see for example Ciari and Axhausen, 2011; Weis *et al.*, 2011).

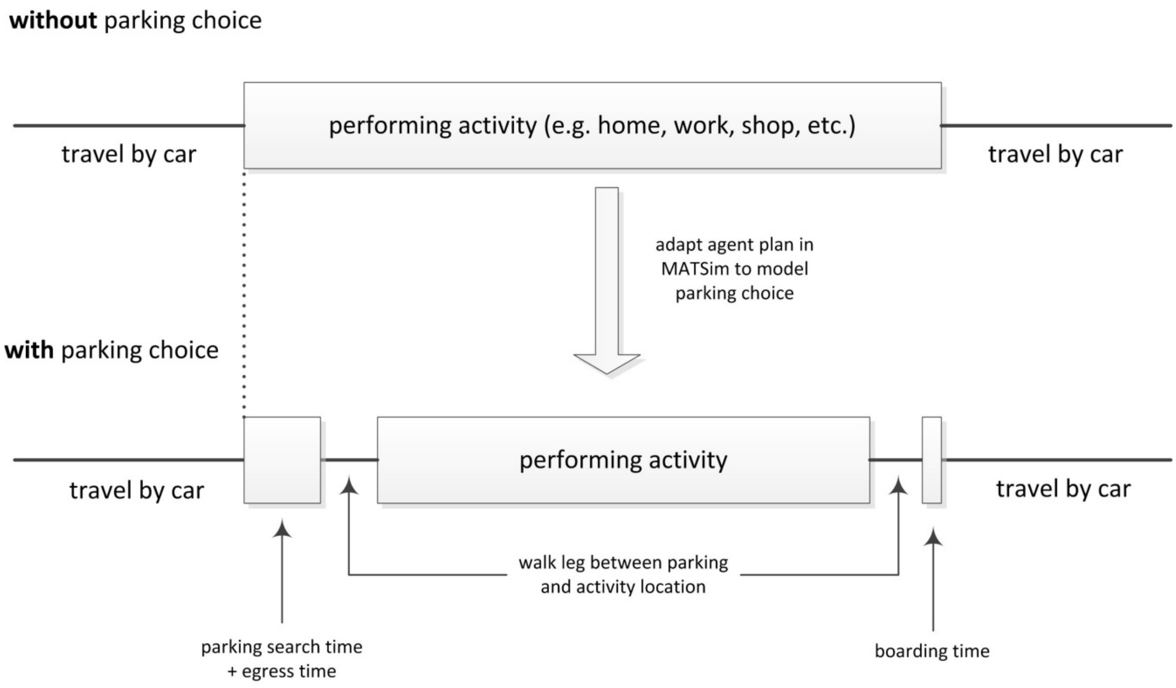
4.3.2 Extending MATSim

The simulation of the parking choice algorithm presented is implemented into MATSim so that it is able to run at the same time/in parallel to the MATSim traffic simulation. This saves time, which is important for large-scale simulations. The information related to the utility scores that have been assigned to agents for the selected parking are also forwarded to the MATSim simulation so that they are added to the overall score of each agent.

For the moment, we decided not to change the micro-simulation of MATSim, but rather to add the parking choice as a separate module. Therefore, a couple of post-processing changes to the agent's plan are necessary, so that the simulation output is consistent with the rest of MATSim (see Figure 4.3). In order to reflect the parking choice decision in the agent's plan, new walk legs are introduced, based on the walking time for each parking choice made. Furthermore, short activities for egress time and boarding time are added to the plan. For the simulations in the next section, we used fixed time intervals of 30 seconds for egress and boarding of the vehicle. Although the parking search time inside garage parking and for street parking is not part of the model yet, the search time could be modeled based on existing models (see Axhausen *et al.*, 1994 for an example). As the time available for performing activities at the destination is reduced, due to parking related activities, the utility function in MATSim also has to be adapted to reflect this change. As a final step, the adapted plans should be simulated again in MATSim for a couple of iterations, with only route choice turned on, so that the parking related trips are part of the final result.

The parking choice algorithm in MATSim has been implemented in a generic way, so that it can be used for different applications. There is a default parking choice strategy implemented, as defined in the description of the algorithm. But if the agent requires a different parking space for certain situations, he or she can do so. E.g., in the city of Zurich it is possible to buy a monthly permit for local public street parking. If information about the ownership of such parking permits is available, this can be incorporated into the model, so that these agents will prefer to park on the street in their neighborhood instead of using parking garages.

Figure 4.3 Changing plans to incorporate parking activities



4.4 Simulations

An existing national scenario of Switzerland for MATSim (Meister *et al.*, 2010) is calibrated for the area around the city of Zurich and then recalibrated after adding the parking model. The calibration without parking is done based on the mode shares, as described in Meister *et al.*, 2010, whereas the calibration of the scenario with parking is described later.

The simulation scenario consists of all agents residing within a 30km circle around a central place in Zurich. In addition to these agents, other agents residing outside the study area, which enter the study area at some time during the day, are included in the simulation. The network used for this simulation is a high-resolution navigation network containing around one million links. For the initial tests presented here instead of simulating a 100% population sample, smaller population samples are used (10% and 1%, which corresponds to 180'000 and 18'000 respectivly). Such a population sampling is a common practice where the network link flow capacities are adapted to match the population sample size. Although a sampling as low as 1% may lead to artifacts, especially due to the scaling of the network links, such a loss in quality is not deemed critical for these initial test experiments. Naturally, the parking capacities are also scaled accordingly.

The transportation modes available in the simulation are car, public transport, bike, and walk, where only cars are physically simulated along the roads. The travel times of the other modes are based on simpler models, such as average speed for biking and walking and fixed travel time matrices for public transport. The agents could change mode, departure time, activity duration, and route. 50 iterations are performed for each simulation, as in the original calibration. The traffic count comparisons of the calibrated model are comparable to those previously reported in Meister *et al.* (2010).

4.4.1 Parking Infrastructure Supply Model

Several datasets are used to model parking supply in the city of Zurich. In order to reduce computation time and memory consumption, on-street parking spaces (ca. 50,000 spaces) are clustered together to form new parking facilities with a parking capacity assigned to them. This results in parking facilities with an average of ca. 6 parking spaces per facility. For the over 100 parking garages containing more than 15,000 parking, no such clustering is performed. The modeling of private parking (over 200,000 spaces) is more challenging, as these spaces need to be assigned to activities in buildings. Several approaches were tried before it was found that it would be best to distribute the private parking proportionally to the activity capacities in the buildings located close to them. Parking supply data outside the city of Zurich is only sparsely available. For the simulations conducted, it is assumed that the parking supply outside of the city is unlimited. Although this is not realistic, still this assumption seems no worse than the original parking model assumption in MATSim, which had no parking constraints at all. Nevertheless, a parking model to be implemented outside the city of Zurich is work in progress (see future work). The pricing of the paid parking is also modeled in a simplified manner. At all garage parking spaces, the price is set to 1.50CHF/h (Swiss francs per hour, or US$ 1.90, according to the exchange rates in July 2011). The price of all on-street parking in central Zurich is set to 2.00CHF/h (this encompasses all on-street parking within a 1 km radius of “Lindenhof”). For the threshold ϑ after which the marginal disutility for walking increases, a value of 350m is chosen based on previous literature. It has been reported that most people park within 350m walking distance in Tel Aviv, Israel and 300m in Leuven, Belgium (Benenson *et al.* 2008; Spitaels *et al.;* 2009).

4.4.2 Calibration

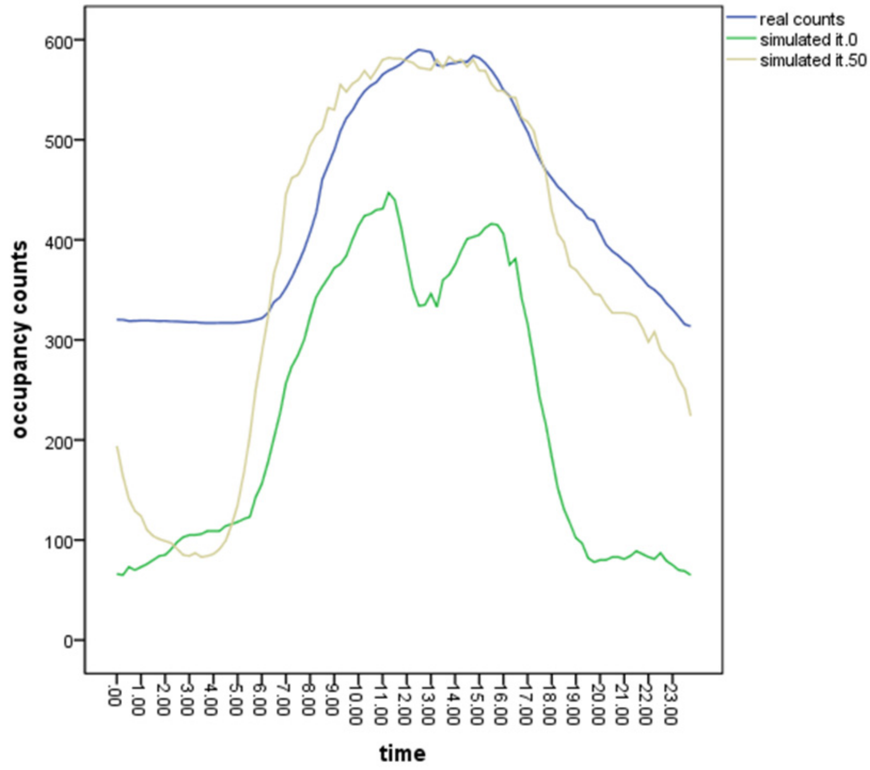
For the calibration of the parking demand, online data about the occupancy of the parking garages is collected from a website (Parkleitsystem Stadt Zürich, 2011) on a minute-by-minute basis, together with parking garage capacities. As there are some inconsistencies between the parking capacity information available on the website and the data received from the city authorities, parking garages are only compared when the parking capacities from both sources matched. Parking occupancy data from 25 such parking garages was chosen randomly for the calibration. As in the scenario, an "average weekday/Wednesday" is simulated, parking occupancy data for the whole day of Wednesday, April 27th 2011 was used for the comparisons.

Due to the uncertain allocation of private parking to buildings/activities, the share of private parking in the model needed to be scaled to match the scenario. Therefore, the total share of private parking in the scenario was adjusted during the calibration until the occupancy at the parking garages in the simulation roughly matched the numbers measured in the real world.

Figure 4.4 visualizes the outcome of this procedure, where the sum of measured and simulated parking occupancy counts are shown at MATSim iteration 0 and 50. As this is a 10% scenario, the numbers are scaled down, so that in reality a peak occupancy of around 6,000 vehicles at the selected parking garages was measured for the day. The general shape of the occupancy according to the garage parking comparison looks good, but too low volumes are reported by the simulation for overnight parking. This indicates that some demand is missing in the scenario. This could be caused by residents parking second and third cars which is not properly captured in the car ownership model we used to describe the agent population.

It is verified that the simulated parking-related walking distance distribution within the city has the expected asymptotic shape. Around two thirds of the agents are parking within 100m of their destinations, and around 95% are parking within 450m. In Spitaels *et al.* (2009) parking walking distance for another European city is reported, with a higher parking-related walking distance: two thirds of the people park within 300m from their destinations. This could possibly indicate that there are too many private parking spaces available, but this has to be verified in the future, e.g., with survey data from Zurich. In the simulation, 1% of the agents walked more than 900m. These long walking distances also require special attention, as they could indicate possible errors in the demand or supply model.

Figure 4.4 Calibration of Counts



4.4.3 Sample Parking Policy

Several tests were performed during calibration that showed that the model is sensitive to various parameters, including parking type, walking distance, and parking cost. In the following section an example is given to demonstrate how the presented parking model could be utilized to design and test a new parking policy.

Let us assume that someone came up with the idea, that one could reduce peak traffic volumes at certain links by reducing parking supply in the city of Zurich. One example of how such a policy measure could be designed and tested with the presented parking choice model is demonstrated here:

1. To simplify this task we only focus on the evening peak hours here. First the top 10% links with the highest traffic volume during peak hours are identified.
2. Afterwards, we identify all agents in the simulation, which travel over these high volume links during peak hour.
3. One idea to reduce the traffic on those high volume links could be to identify where the agents selected in the previous step perform activ-

ities and reduce parking supply in those areas. To do so, the locations of the previous and next activity related to the trip leading over the high volume link during peak hour are identified for the selected agents. If any of those activities is located inside the city, we mark that activity location for consideration in the next step.

4. In this step, areas are identified where many of those agents perform activities, who contribute to the traffic volume during peak hour on the identified links. Clusters of the activity locations identified in the previous step are formed, and the clusters with the highest number of activities are chosen.
5. In order to reduce parking supply, public parking is reduced in the selected areas/clusters.

Experiment

For this experiment, a 1% population sample is used to execute the simulations faster. The evening peak hours are defined as 16:00 to 19:00. The cluster radius is chosen as 500m. The four clusters with the highest numbers of activities are selected, which corresponds to ca. 2200 to 3800 activities per cluster when extrapolating it to a 100% population sample.

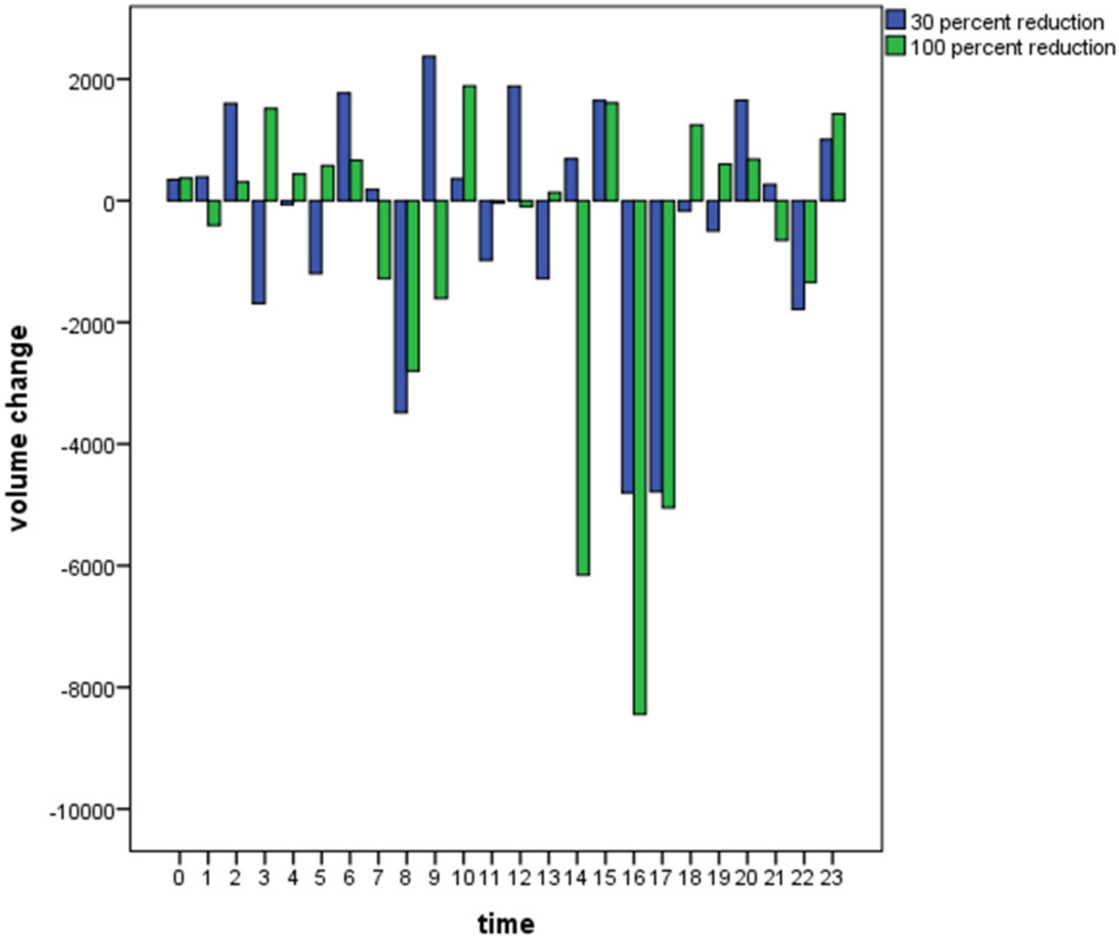
In order to demonstrate the potential of the policy measure, two experiments are performed. In the first experiment, 30% of the public parking spaces in the identified clusters are removed. In the second experiment, all public parking spaces from the identified areas are removed.

Result

In Figure 4.5 the volume change for the top 10% high volume links is shown after applying the measure. It can be observed that the highest reduction in traffic volumes happens during the evening peak hour at the selected links. As the results show, at least some agents decided to shift their mode. As MATSim is an iterative process, where agents always try to find faster links for travelling, it is not surprising that the volumes at the selected links also change throughout the day. But this also raises a question: Is the change in volumes just random, due to the iterative nature of MATSim? It seems unlikely that the high reduction in traffic volumes is just random, but more runs must be performed to determine how much, if any, of this volume change is brought about by random changes of plans of agents in MATSim.

Although this experiment is conducted by looking at high volume links, one might also look at high congestion links instead where the average speed driven is much lower than the maximum allowed driving speed. It could be interesting to see how much influence such a measure would have on the travel time in the system and how much the average speed at congested links could increase due to such a policy change.

Figure 4.5 Changes in traffic volumes after reducing parking supply in selected areas of Zürich



One replanning dimension, which is not available to the agents in the simulations conducted, is location choice. E.g., due to the parking reduction, people who are going to shop in one location might shop somewhere else. This possibility might be added to future runs, as described in Horni *et al.* (2009).

Real world policies are often based on political discussions, feedback from residents, and shop owners. Also, in this setting, the reduction in parking can be based both on output from such a parking choice model and the interests of the general public. The presented model could be used to evaluate the possible implications of the various policy options under discussion.

4.5 Discussion and Future Work

4.5.1 Improve the Parking Model for Zurich

We plan to improve the presented scenario for Zurich in several ways.

- A new Zurich Scenario has recently been calibrated for MATSim. It contains several improvements such as addition of freight transport and a detailed micro-simulation of public transit (Horni et al., 2011c). This new scenario could be tested with parking choice in the future to compare how the different parking indicators, e.g., parking occupancy, changes.
- Parking supply data outside the city of Zurich also needs to be improved. This data can come from national surveys, local government or imputation models.
- The parking supply model inside Zurich can be improved in several ways. The current pricing is too simplistic to reflect spatial differences in price. Actual prices are available for garage parking and metered street parking; which should be incorporated in the future. Furthermore, a division of street parking into several categories could be made, as some data on this is also available.
- At the moment, we only look at the sum of occupancies at the garage parking for calibration. But real occupancies at public garages show that there are huge differences in the shape of the occupancy curves at different garages over the course of a day. In the future, we could also take such spatial differences into account. To improve the calibration and validation of the model, additional data needs to be collected, such as the occupancy log at the metered on-street parking. Such data should be available for metered street parking from the city authorities. Furthermore, data parking-related walking distances would need to be included in future surveys from urban areas for Swiss cities in particular.

4.5.2 Improving Parking Choice in MATSim

Although the model presented is agent-based, in the presented scenario the attitude of all agents towards parking was the same. This should change in the future, starting with the addition of income data to the Zurich scenario and with an improved model for the parking cost utility. Also, additional information from city authorities, such as where people who have paid for a monthly public street parking permit live, needs to be integrated. Furthermore, people's attitude towards illegal parking could become a part of the parking utility function; the level of law enforcement could also be taken into account. A model for the disposition of people towards illegal parking could be based on real data from Zurich.

Another issue, which is not present in the presented model, is the notion of incomplete parking information. In Khattak and Polak (1993), the effect of parking information services on a traveler's behavior is discussed, and it is demonstrated that there are demographic differences in the usage of such information. In Bovy and Stern (1990) it is also discussed that not all parking garages and on-street spaces are known to people. Therefore, the selection of a parking lot is based on a subset of all existing/available parking. This has not been considered in the current chapter, however such an extension should be investigated further.

4.5.3 Adding Parking Search

Many of the ideas presented in the parking choice algorithm can be reused in the context of parking search. It is planned that the current model should be extended/adapted in the future to include parking search as well, so that a high demand for car travel at a destination could be reflected also in terms of increased parking search-related traffic in that area, as is often reported, e.g. Huber (1962).

4.6 Conclusions

In this chapter, a new parking choice model is proposed, implemented into an existing travel demand simulation, and initial simulations with over 100'000 agents are presented. The results show that the parking choice model can help to improve the existing traffic model, so that replanning of the agents can take parking occupancy, walking distance and price preferences into account. Furthermore, the model presented also forms a foundation of additional work, which the authors are pursuing in Waraich *et al.* (2009b), where the potential future electricity demand by electric vehicles is modeled. For such an application, the presented parking choice algorithm provides the parking choice hierarchy and parking types, which are necessary, as a generic parking model is not enough. The presented parking choice model is just the beginning of a series of improvements for MATSim, and adaptions of the model are planned to aid the implementation of a wide range of policy design.

Chapter 5

Optimizing Parking Prices using an Agent-based Approach

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5.1 Introduction

Based on studies conducted in several cities around the globe, it is estimated that on average one third of city center traffic is parking search traffic (Shoup, 2004). A main reason for cruising for parking is obviously that parking demand is close to capacity or even exceeds it temporarily. A major instrument that policy makers have for balancing supply and demand is adjusting parking price. But the question is, how to get the price for parking right?

Pricing parking correctly is not a new problem: Vickrey suggested in 1954, that parking should be priced in a way so that a parking place is available for those willing to pay for it. He suggested 15% free parking at all times, which corresponds to a couple of free parking spaces for the usual city block. Furthermore, he argued that there should be no minimum price for parking. If even at price zero a 85% occupancy cannot be reached, parking should be offered for free (Vickrey, 1954). Shoup developed the ideas of Vickrey further and suggested that the issue of finding the optimal parking price can be solved incrementally by increasing/decreasing the parking price for curb parking until around 85% of parking spaces are occupied at all times (if possible), with possibly different price levels at different times of the day (Shoup, 2004; Shoup 2006).

Exactly such a system was implemented in 2010 in parts of San Francisco, called *SFpark* (SFpark, 2012), where parking sensors have been installed on 8,200 on-street parking spaces. By using parking occupancy data from these sensors the parking rates are adjusted no more than once per month. These rate adjustments are small, such as $0.25 to $0.50 per hour and are also applied to city-owned garages, where many empty spaces are often available. The parking price also varies over the day and between working days and weekends.

Although the SFpark experiment seems to achieve the desired effects in some areas of the city, some unexpected effects have been observed on some roads, for example rising demand with rising prices and falling demand with falling prices (Cooper and McGinty, 2012).

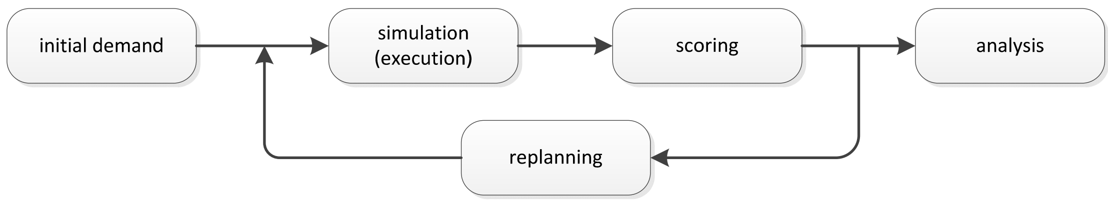
In order to investigate the possible effects of such “parking price optimization” in other cities we describe a parking model in the next section, which we use to simulate an application of Shoup’s approach to the city of Zurich. This application demonstrates that the model presented is able to tackle the relevant aspects of the problem at hand. After a brief discussion including future work we draw some conclusions.

5.2 The Parking Model

The parking model presented extends previous work by the authors on agent based parking choice modeling (Waraich and Axhausen, 2012b). In the work of Waraich et al. (2012), a combined parking choice and search model is described. In the following, we only present the relevant parts of the model for its application within the parking price optimization context.

Both parking models mentioned above are integrated into the agent-based travel demand simulation MATSim (MATSim, 2012). Figure 5.1 shows MATSim's co-evolutionary iteration process (Holland, 1992): each person in MATSim is modeled as an agent, which has a daily plan of trips and activities such as going to work, school or shopping. Furthermore, each agent has several modes of travel available in order to travel between activity locations, such as car, walk, public transit and bike.

Figure 5.1 Co-evolutionary simulation process of MATSim



The process starts with an initial plan for each agent and its goal is to find an optimal plan for all agents simultaneously. The first step in each iteration is traffic simulation: the plans of all agents are executed by a micro-simulation, resulting in traffic flows along network links. After this simulation, the execution of the agent's plan is scored and assigned a utility. For example, a person with a lower travel time has a higher utility than one who has a longer travel time because of being caught in a traffic jam. Furthermore, performing activities such as being at work increases the utility. The goal of each agent is to maximize the utility of its daily plan. During the replanning step, the agent can reselect or adapt a previously executed plan for execution in the next iteration. Plans with a higher utility score have a higher change of reselection, while plans with bad scores are deleted over time, as only a limited number of plans per agent is kept. This corresponds to survival of the fittest in a co-evolutionary algorithm. The replanning algorithm has several degrees of freedom, such as changing routes, departure time, travel mode or the location choice of agents. The execution of all plans, the scoring and the replanning is called an iteration. This iterative process approaches a point of rest corresponding with a stochastic user equilibrium called relaxed demand. More details about the conceptual framework and the optimization process of the MATSim toolkit can be found in (MATSim, 2012).

5.2.1 Utility Function

An explicit utility function of parking is important for several reasons in our context, although some other agent-based parking models do not use one, e.g. Algers et al. (1995). First the parking utility function is needed for comparing different parking places to each other, e.g. price or walking distance. Secondly, the utility function allows the use of personalized taste parameters, which are estimated, e.g. from stated or revealed choice observations. This is evidently important, as people do not only value different components of parking differently, e.g. search time, walk time and parking cost (Axhausen and Polak 1991; Hess and Polak, 2004), but clearly when it comes to parking policy the reaction of people is not homogeneous (Jovivic and Hansen, 2003). A third reason for using a utility function within the MATSim traffic simulation context is that the parking decision of the agent should influence its other decisions, e.g. location or mode choice.

The utility function of a specific parking choice for agent i is formulated as in Equation (5.1), where the individual preferences of the agent with regards to parking cost, search time and walk time are considered. The ϵ_i is the random error term. This parking utility function can be extended to contain additional utility terms as required.

$$U_{parking,i} = U_{P_{cost},i} + U_{P_{searchTime},i} + U_{P_{walk},i} + \cdots + \epsilon_i \qquad (5.1)$$

Now, when the agent selects a parking space, its utility is added to the overall utility function in MATSim, which now looks like Equation (5.2):

$$U_{plan,i} = \sum U_{travelTime,i} + U_{travelCost,i} + U_{performActivity,i} + \cdots + \sum \boldsymbol{U_{parking,i}} \qquad (5.2)$$

By adding the parking utility to the overall utility of the agent, the parking choice has an impact on the other choice dimensions of the agent. For example an agent that gets a bad parking utility score at a certain destination might change the travel mode for reaching that activity location or even change the activity location, if it is a secondary activity location such as shopping.

5.2.2 Parking Selection

In order to model parking selection, an attempt is made to mimic the SFpark scenario. In that scenario, parking prices can be different per street block and vary throughout the day. Additionally, the price can change monthly. It is clear that having different prices on neighboring roads and varying throughout the day is quite complex and therefore probably discourages random parking search behavior. SFpark provides users with complete information about free public parking spaces in real-time.

We have implemented a similar agent behavior in our model where agents search for parking using smartphones. An agent assigns a utility score to each of the free public parking spaces in the surrounding of the destination using its personal utility function and selects the free space, which gives it the highest utility score. As in this case there is no parking search, the agent is trading off between walk time and parking cost only. In reality this procedure could be fully automated, such that people are guided towards parking that best matches their preset criteria both in terms of walking distance and price. In order to keep our model simple, we assume that the parking space is reserved by the mobile device a couple of minutes/blocks before approaching that parking space. However this assumption could be removed easily in an extended version as described in the discussion section.

5.2.3 Parking Fee Adaptation

In order to simulate the change in parking fee and the reaction of agents to this change, two approaches seem possible. A first approach could be to run the traffic simulation until the demand is relaxed, and then adapt the parking fee before running the traffic simulation again. This process could be repeated until the parking fee converges. A second approach is to change the price after each iteration. The first approach is slower than the second one, but the second approach has to be applied with care in order not to put too much change into the system, so that it cannot relax.

The second approach is adopted here as it is faster and the volatility in the system can be adjusted, for example by changing the price not after each MATSim iteration, but instead less often to give more time for the system to react to prices. As shown in the simulations in the next section, the MATSim relaxation process is not endangered by this approach, as only local traffic patterns close to the destination are changed due to such parking price changes.

5.3 Simulations and Results

In order to test our model, we use an existing Zurich MATSim implementation (Waraich and Axhausen, 2012b) as a starting point. As only parking within the city of Zurich is of interest here, only such agents that reside or travel within a eight km radius around a central place in Zurich ("Quai Bridge") are part of the simulation. As this study does not focus on travel patterns or search related traffic changes, a planning road network of Switzerland with around 60,000 links is used, instead of using a high resolution navigation network. For the initial tests presented here, instead of using a 100% population sample, only a 10% population sample is used with around 72,000 agents. In order to account for this population sampling, link flow capacities in the network and parking capacities are also adapted to match the population sample. Although such population sampling may lead to artifacts due to the scaling in the network and especially the street parking capacities, for the presented initial experiments such loss in quality is not deemed critical. This issue is further discussed in the future work section.

The travel modes available in the simulation are car, walk, bike and public transit. However, from these only the car mode is micro-simulated along roads. The travel times for the other modes are based on simpler models, such as average speed for bike and walk and a fixed travel time matrix for public transport. From iteration to iteration the agents can change travel mode, departure time, activity duration and route. After 100 iterations the scenario is then deemed relaxed, as indicated by the small plan changes respectively utility score difference between the best and the worst plan in that case which is shown later in this section.

5.3.1 Agents' Preferences

The household income distribution of agents is based on census data from the canton of Zurich (Vrtic and Axhausen, 2003). For modeling the agents' preferences towards parking, data from a previous stated choice survey is used (Vrtic and Axhausen, 2004). That survey yielded data from 1,034 Swiss residents. The questions, aiming to assess the influence of parking on location and mode choice, are combined with a stated choice survey comprising experiments for the following decisions, each of which contain variables describing parking supply:

- the choice of a parking space at a shopping or leisure location;
- the choice of a destination for carrying out a shopping or leisure activity;
- the choice of a mode for carrying out a commute, shopping or a leisure trip.

Based on the survey data, discrete choice models are estimated to determine the respondents' valuations of the various attributes related to parking (cost, search and walk times). The models are estimated in willingness-to-pay (WTP) space; the utility functions are formulated in a way to directly yield the WTP measures for the attributes of interest (Train and Weeks, 2005). The WTP measures calculated are those for car and transit travel times, also known as the values of travel time savings, or VTTS. Furthermore, the WTP for reductions in parking search time is also measured.

The utility functions for the MNL model include non-linear interaction terms, which follow the formulation introduced first in the study by Mackie et al. (2003). It has been applied in several Swiss studies (Weis et al., 2010; Hess et al., 2007; Axhausen et al., 2007; Axhausen et al., 2008) and underlies the current Swiss value of travel time savings guidelines (Swiss Association of Road and Transportation Experts, 2007). It extends the standard linear utility formulation by allowing continuous interactions between variables, which explains a portion of the heterogeneity manifested by respondents when evaluating choice experiments. As stated by Hess et al. (2007), this methodology has various advantages over arbitrary segmentation into discrete groups, such as the deterministic computation of taste heterogeneity and the considerably faster estimation compared to random coefficient approaches.

The general specification of the utility function is as follows:

$$f(y,x) = \beta_x \cdot \left(\frac{y}{\bar{y}}\right)^{\lambda_{y,x}} \cdot x \qquad (5.3)$$

where:

x = (dis)utility generating variable, such as travel time or cost;

β_x = utility parameter associated with x, to be estimated;

y = variable assumed to interact with x, such as income or trip distance;

$\bar{y}$ = reference value for variable y, such as the sample mean or median;

$\lambda_{y,x}$ = elasticity of the influence of y on the (dis)utility generated by x, to be estimated.

The respondents' valuation of attribute x is thus assumed to vary with the value of attribute y. Normalizing y assures that the estimate of the linear parameter indicates the valuation of x at the point of normalization (as the interaction term then equals one).

In the present case, the following interactions are assumed:

- between travel cost and VTTS;
- between trip distance and income;
- between parking cost and the WTP for parking search time;
- between the duration of stay at the destination and income.

The interactions for the VTTS measures correspond to a re-formulation of those proposed in Hess et al. (2007), whereas the specification for the parking search time WTP is novel and related to the subject of the present study.

A total sample of 14,499 observations was used for model estimation. The parameter estimates are shown in Table 5.1 along with the corresponding t-statistics, where values above 1.96 indicate that the parameter is significant at the 95% level. Goodness-of-fit statistics are also shown. The model performs very well in terms of model fit, with an adjusted ρ^2 of over 0.4. The interaction parameters indicate the existence of taste heterogeneity for the corresponding variables.

All linear parameters are of the expected sign and most are significant at the 5% level. Various socio-economic characteristics are included in the utility functions for the mode choice component (results for car and transit are found in the first two parts of the table respectively). Male respondents have a higher tendency to choose the car. The availability of mobility tools has the expected positive influence on the propensity to choose the corresponding mode: transit pass owners prefer to travel by transit, while respondents that always have a car at their disposal tend to favor travel by car. Increasing vehicle headways and transfers between vehicles reduces the utility of the transit alternative. For the MNL model, the interaction parameters indicate that the sensitivity for price increases is lower for persons with a high income and for longer trips. Thus, the VTTS increases with these interaction variables.

Table 5.1 Model Estimation Results

Attribute	Parameter	t statistic
Car VTTS (in Swiss Francs per minute)	0.717	1.40
interacted with trip distance (in kilometers)	0.233	1.28
interacted with income (in Swiss Francs per month)	0.946	3.47
Fuel cost (in Swiss Francs)	-0.066	-1.68
interacted with trip distance (in kilometers)	-0.062	-0.39
interacted with income (in Swiss Francs per month)	-0.904	-3.38
Parking search time WTP (in Swiss Francs per minute)	0.604	12.96
interacted with duration of stay (in minutes)	-0.334	-10.17
interacted with income (in Swiss Francs per month)	0.092	1.22
Parking cost (in Swiss Francs)	-0.129	-18.4
interacted with income (in Swiss Francs per month)	-0.067	-1.65
Trip purpose: shop (reference category: commute)	0.928	7.46
Trip purpose: leisure (reference category: commute)	0.120	1.00
Gender: male (reference category: female)	0.435	4.41
Car always available	1.380	9.74
Transit VTTS (in Swiss Francs per minute)	0.431	3.50
interacted with trip distance (in kilometers)	0.455	3.14
interacted with income (in Swiss Francs per month)	0.318	1.49
Ticket cost (in Swiss Francs)	-0.114	-3.77
interacted with trip distance (in kilometers)	-0.401	-3.48
interacted with income (in Swiss Francs per month)	-0.315	-1.75
Number of transfers	-0.304	-6.01
Headway (in minutes)	-0.020	-9.19
Transit card: Half-fare (reference category: none)	0.493	2.89

Transit card: Generalabonnement (reference category: none)	1.040	4.20
Walk travel time / acces and egress time (in minutes)	-0.118	-20.16
Bike travel time (in minutes)	-0.151	-13.74
Parking type: open lot (reference category: on-street)	0.075	1.60
Parking type: garage (reference category: on-street)	0.192	3.96
Location type: outskirts (reference category: city center)	-0.245	-6.40
Pricing level: medium (reference category: low)	-0.003	-0.06
Pricing level: high	-0.341	-7.39
Cost-performance-ratio: good (reference category: adequate)	0.055	1.22
Cost-performance-ratio: very good (reference category: adequate)	0.284	5.85
Constant: abort search	-4.300	-21.14
Constant: bicycle (reference category: walk)	-0.536	-2.17
Constant: car (reference category: walk)	-3.150	-13.30
Constant: transit (reference category: walk)	-1.110	-3.81
Scale parameter: parking choice (reference category: mode choice)	1.270	4.11
Scale parameter: location choice (reference category: mode choice)	1.010	0.24
Null Log-Likelihood	-19,817	
Final Log-Likelihood	-11,547	
Adjusted ρ^2	0.415	
Number of observations	15,459	
Run time for estimation	2 hours	

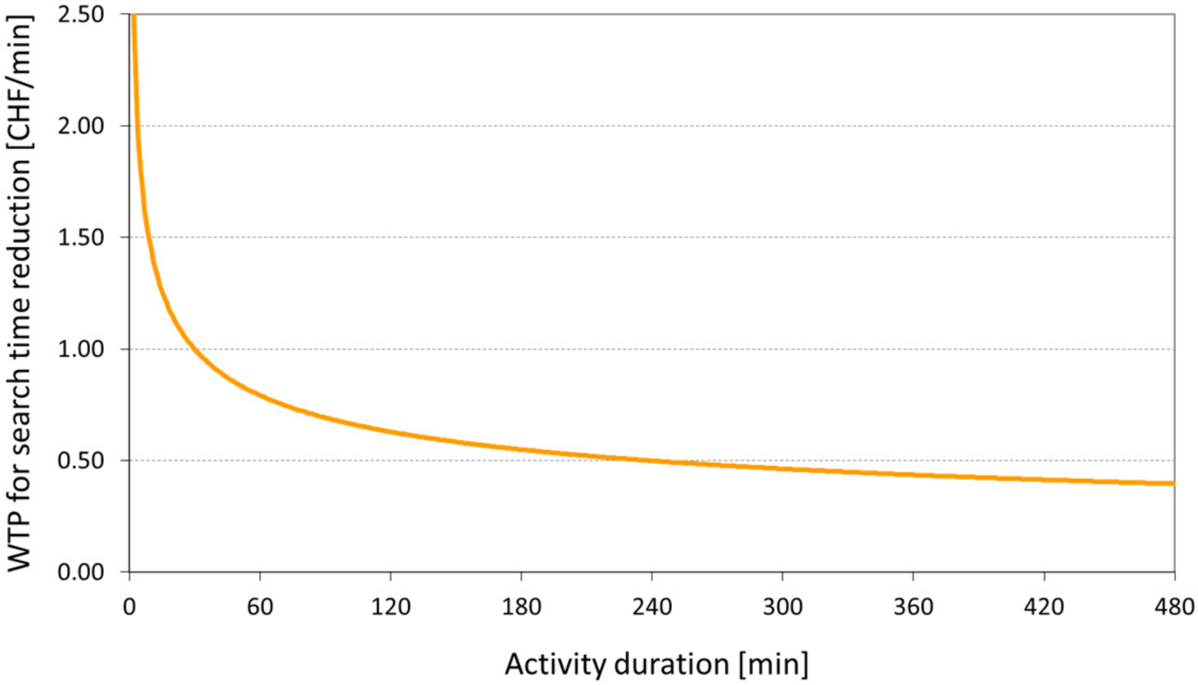
For the parking attributes most variables have the expected effects. Quite surprising is the fact that parking in a garage is preferred to on-street and open parking, as indicated by the corresponding positive parameter. Respondents prefer to conduct shopping and leisure activities in a city center rather than in the outskirts. Low pricing levels and a good cost-performance ratio both increase the utility of a location. Aborting the search for a parking space or an appropriate location and cancelling the corresponding activity is very negatively perceived and only an option in extreme cases. The mean WTP for the avoidance of such a scenario, which may be interpreted as the average opportunity cost of a forfeited activity, can be computed by dividing the constant by the parking cost parameter, and amounts to roughly 30 Swiss Francs.

Search times are perceived negatively, as is evidenced by the positive WTP for their reduction. With increasing duration of stay at a location however, the negative effect of having to search for a parking space is considerably reduced as shown by the corresponding negative interaction parameter. Thus, the WTP is high for very short activities, and steeply decreases as the activity duration rises. Figure 5.2 shows the functional form of the described relation and it can be seen that reductions in search time are particularly valuable at the lower end of the curve, where they amount to up to 2.50 Swiss Francs per minute. Similarly to the VTTS mentioned above, the WTP for search time reductions slightly increases with the respondents' income, as evidenced by the positive sign of the corresponding interaction parameter.

5.3.2 Zurich Parking Supply Data

After detailed elaboration regarding how taste heterogeneity and preferences of agents towards parking are modeled, we continue with description of the parking supply data used. For Zurich the data includes 50,000 on-street parking spaces and over 16,000 parking spaces in more than 100 garages around the city. Furthermore there are over 200,000 private parking spaces in and outside buildings in Zurich. These private parking spaces are assigned to buildings and activities in the model. For example, some parking might only be used by residents and others only by offices or shops, which are located in the same building. For a more detailed description of the private parking supply, see Waraich et al. (2012b).

Figure 5.2 Willingness-to-pay (WTP) for search time reductions as a function of activity duration



The current on-street parking fees in Zurich depend on the location of the parking (high tariff zone vs. normal tariff zone), but most of the on-street parking places in the city are marked blue (*blue zone*) and are as such usable by people in the following ways: residents can buy a relatively cheap annual ticket for their neighborhood and park there without further payment; visitors can also park there free for one hour using a parking disk; and during the night and on Sunday the parking is free even without parking a disk. The hourly parking prices for both the on-street and off-street public parking are based on the data from an earlier study (Oswald, 2012).

5.3.3 Experiments

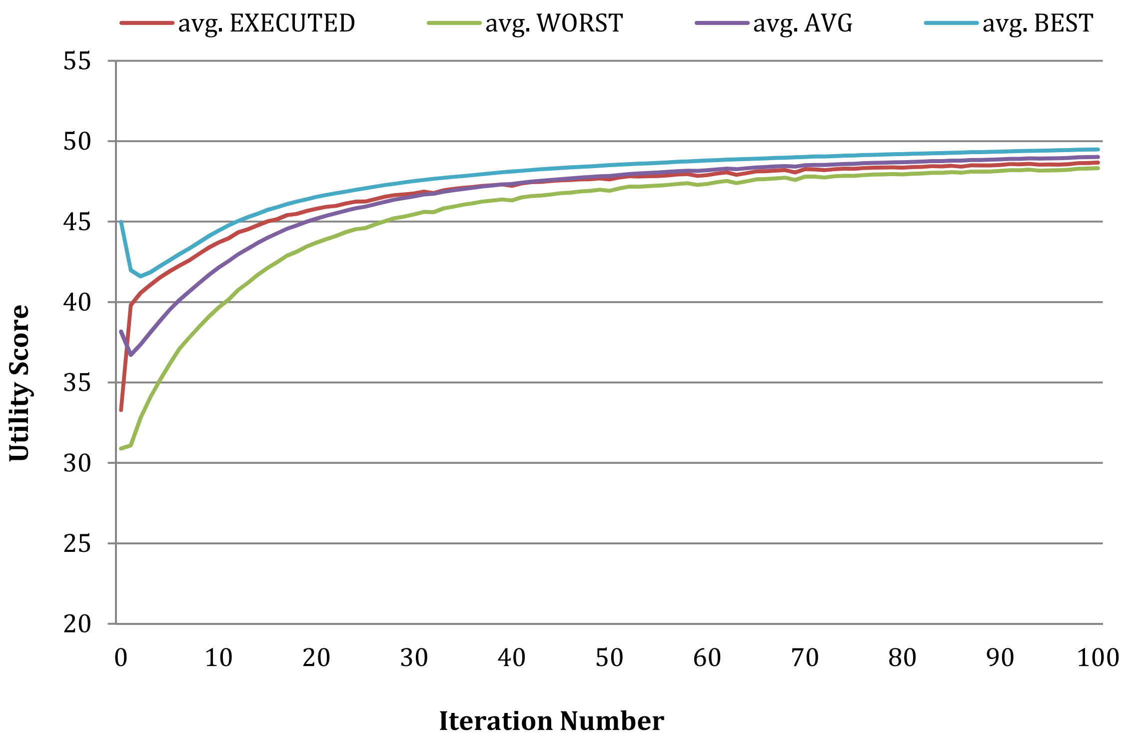
The simulation is started with the current prices for all public parking. After each iteration, if a set of parking spaces had more than 85% occupancy in the previous iteration, its price is incremented by 0.25 CHF/h (Swiss Francs, US$ 0.29 at March 2014 exchange rates). If the occupancy is less than 85%, the rate decreases by 0.25 CHF/h. For street parking, 85% occupancy means the occupancy of a group of spaces, e.g. a block/street. For garage parking the total parking facility capacity is used for this calculation. The initial parking price for the blue zones is set to zero.

This experiment attempts to discover how parking fees could develop if fees are optimized for all publicly accessible parking in the city in the way mentioned above. In these experiments the price is changed for two time periods, not four as in SFpark, where there are three different prices during the day and no fee during the night. For simplicity of the scenario, one price is used for the first half of the day (midnight to noon) and a second price for the second half (noon to midnight).

Relaxation

In Figure 5.3 the score of the agents' plans are shown after each iteration for Zurich scenario described above. The picture clearly shows that the plan scores improve rapidly in the beginning and then slow down as the system relaxes. The picture also shows that our approach to changing the parking price after each iteration does not cause such changes to agents' plans that would cause the simulation to fail to relax.

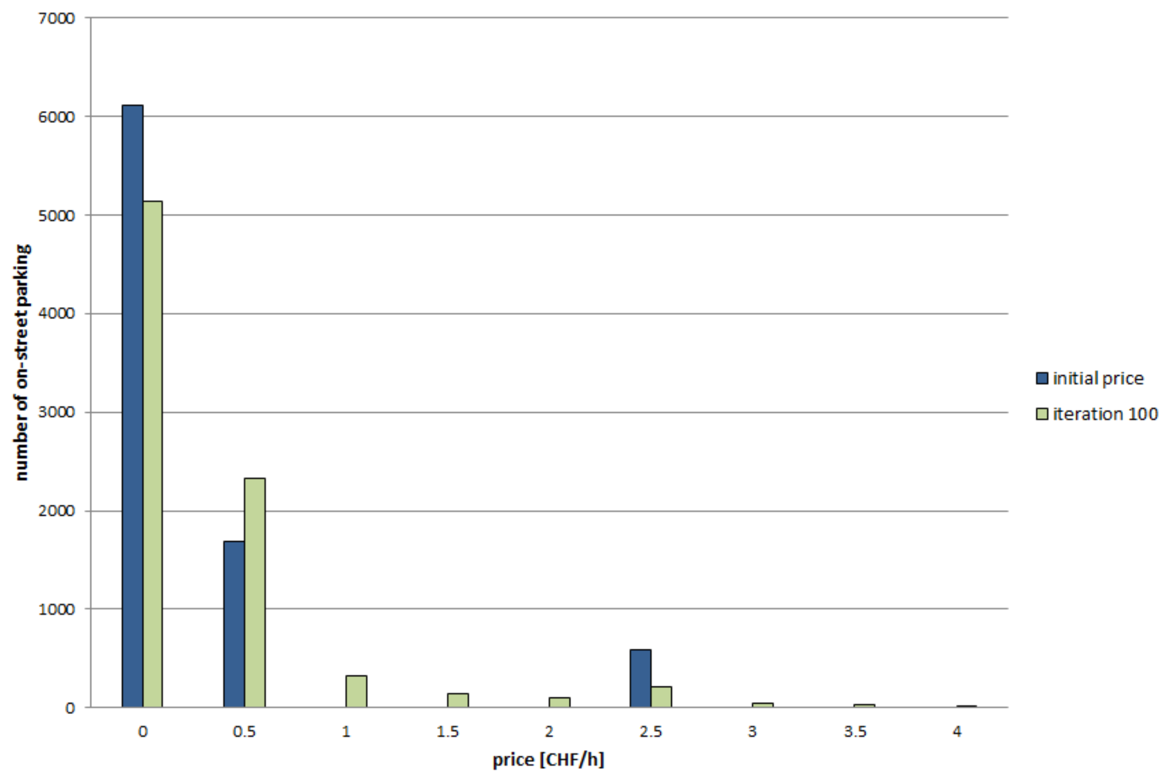
Figure 5.3 Scores of agent's plans at each iteration



Morning Parking Fee Change

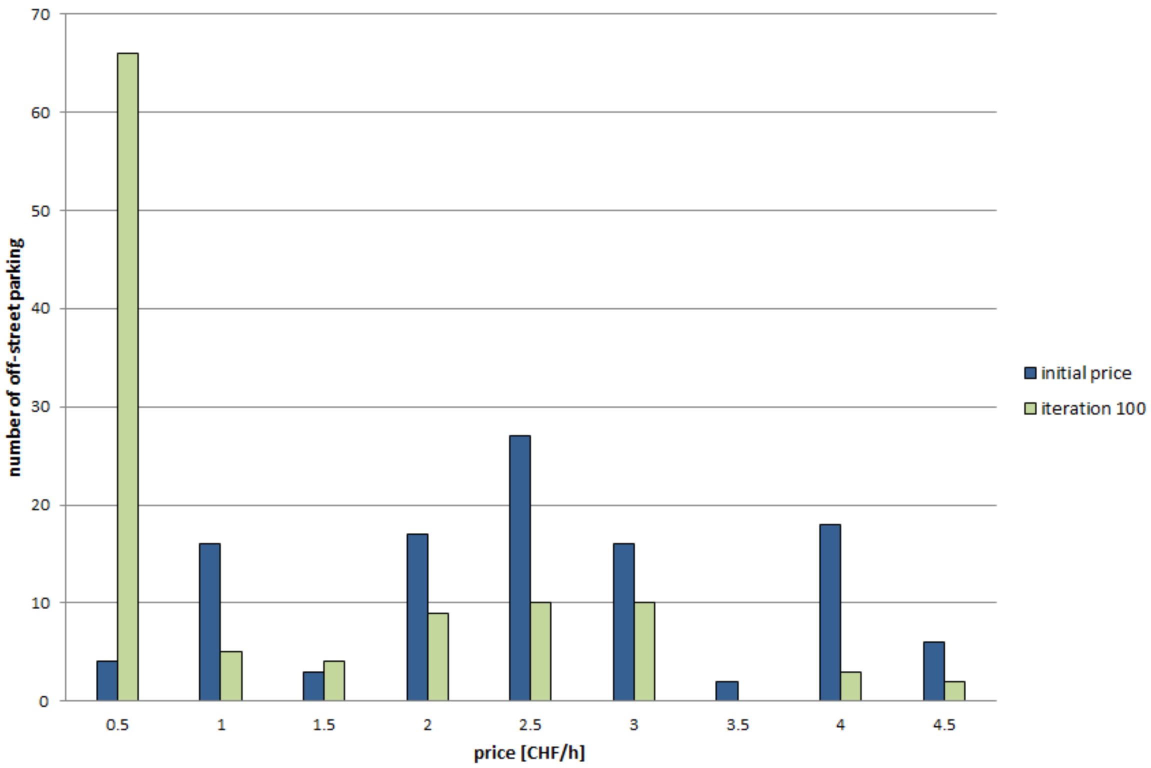
In Figure 5.4 the current and optimized on-street parking price distribution for the morning period is shown. For the initial price one can clearly distinguish the following three groups of parking: the non-metered blue zone parking, the low tariff (0.5 CHF/h) parking and the high tariff (2.5 CHF/h) parking. The optimized on-street parking price is on average 29% higher than it was initially. Here only prices up to 4 CHF/h are shown, although there are a handful of locations with higher fees up to 9 CHF/h (for better visualization, 0.3% of the data is not shown).

Figure 5.4 On-street parking price distribution per hour initially (iteration 0) and for iteration 100



Looking at the price development for off-street parking (Figure 5.5), an opposite trend is observed: the average parking fee at the different parking garages fell by 59%. Initially on average a garage parking space cost around eight times more than an on-street parking space. After price optimization, a garage parking space only costs on average around three times more than an on-street space. Due to this decrease in average garage parking price, the usage of garage parking has increased and the usage of street parking has decreased slightly.

Figure 5.5 Off-street parking price distribution per hour initially (iteration 0) and for iteration 100



Price Difference Morning vs. Afternoon

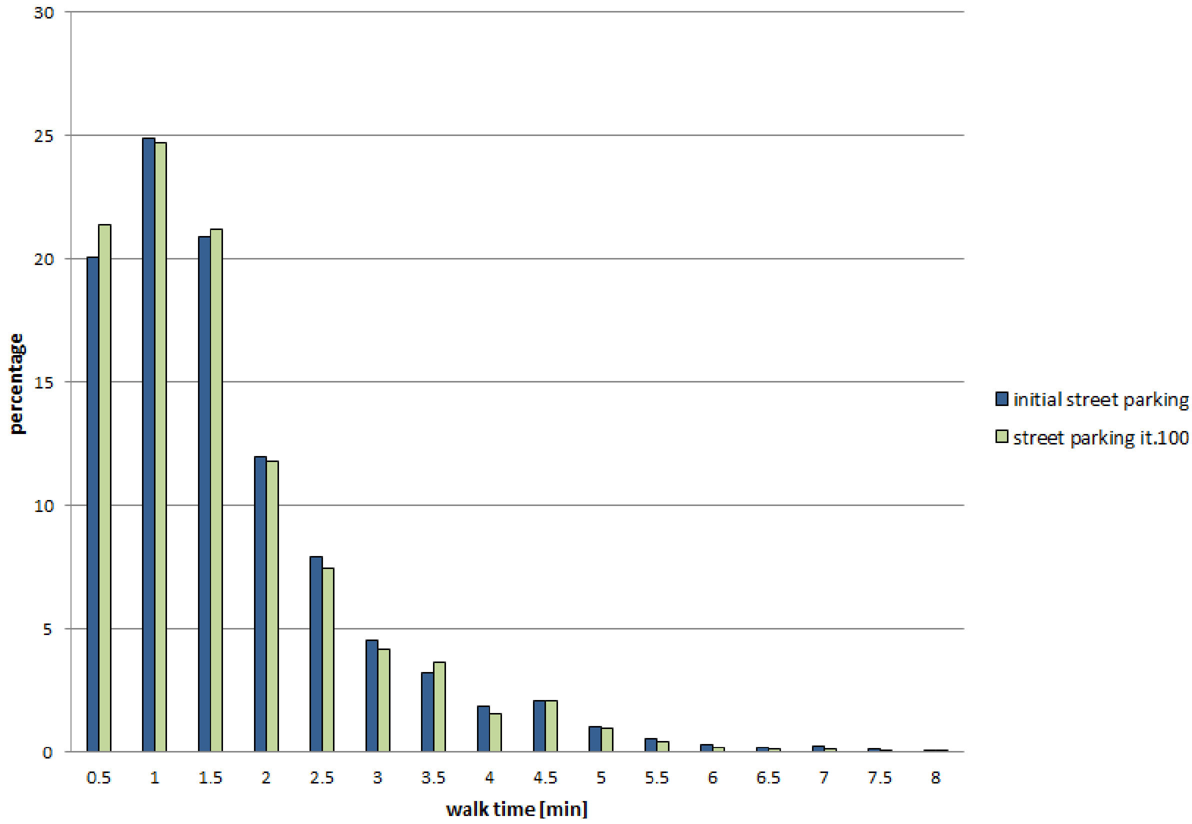
The fees reported above are for the morning. The afternoon fees do not have a significantly different distribution, but they are still different. For on-street parking, 15% of the parking fees are different for the same parking places in the afternoon. Furthermore on average, the on-street parking fee in the afternoon is 18% lower than in the morning.

For garage parking, there are only two garage parking (2%) that have a different price in the morning, than in the afternoon, and therefore the average price does not change significantly.

Walk Times

For walk times between the activity location and the parking place, a clear difference between on-street and garage parking is observed. For on-street parking (Figure 5.6), the average walk time is 1.1 min (corresponding to 77 meters) for both the initial and optimized parking price scenarios. The maximum walk time is around 13 min (for better visualization, 0.2% of the data is not shown).

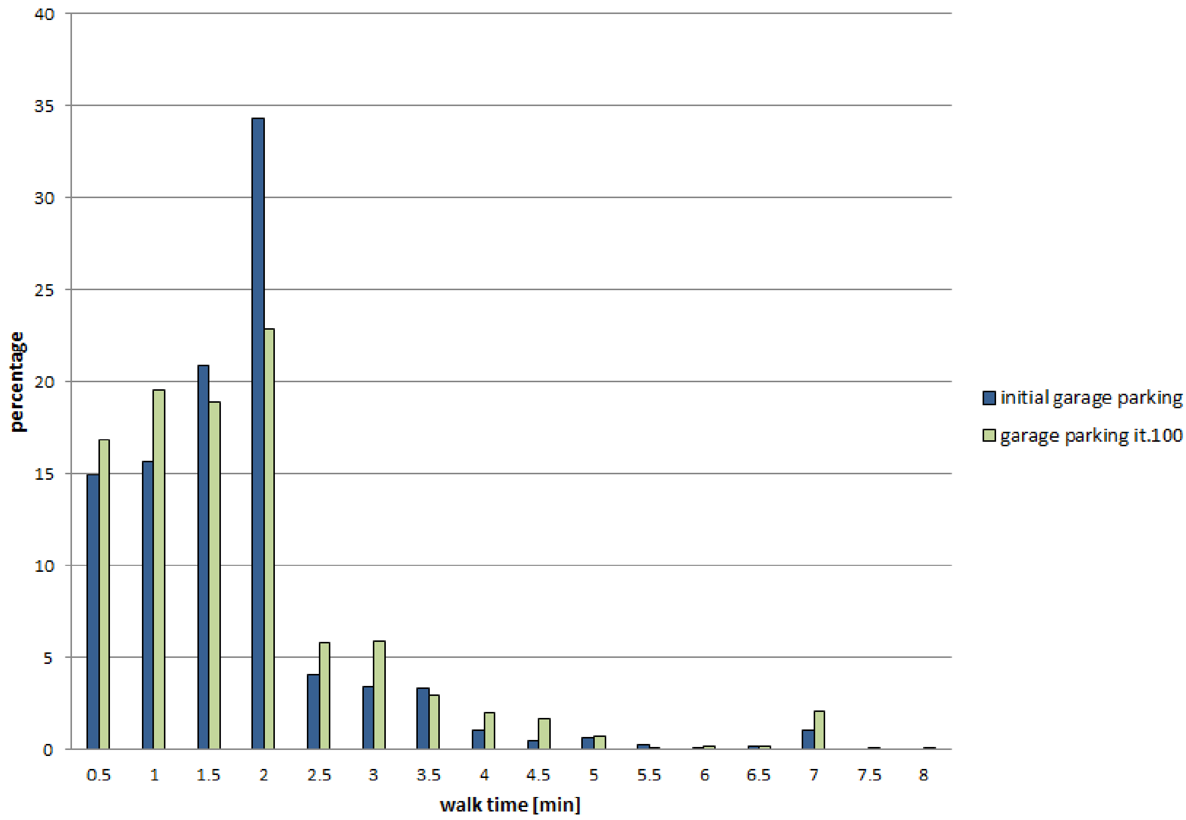
Figure 5.6 Walk time distribution for on-street parking initially and after price optimization (iteration 100)



For the garage parking (Figure 5.7), the initial median walk time is a bit higher than for on street parking. For the initial case it is 1.5 min, while for the optimal pricing case it is slightly reduced to 1.4 min. The maximum walk time is around 10 min (for better visualization, 0.3% of the data is not shown).

When comparing the initial walk distance for on-street and garage parking, it is observed that the on-street parking distribution has a thicker "tail". One explanation for this phenomenon is that outside the city center an off-street parking alternative is often not available and when there is high demand, people have to walk longer distances. On the other side, when looking at the distribution "tail" of the initial garage parking walk times and those in the optimal case, it is observed that due to the price decrease of garage parking its competitiveness increases, as compared with on-street parking more people are willing to walk longer distances to reach a garage parking than with the initial pricing.

Figure 5.7 Walk time distribution for garage parking initially and after price optimization (iteration 100)



It was investigated whether there is any correlation between income and walking distance for the initial or the optimized pricing. When one looks at small test scenarios with single destination test scenarios, one clearly finds such a correlation (see Oswald (2012) for example). However, no such correlation could be observed, neither in the original pricing nor the optimized pricing case. A possible explanation for this could be that in the original pricing case, due to the flat pricing for on-street parking, there is little competitive advantage for higher income agents. But even for the optimized parking price case, it is not necessary the case that a higher income will lead to a significantly shorter walking distance. For example, even if two persons have the same activity location, the person with the higher income might still be willing to walk longer if that person wants to park for a longer duration. This issue is further discussed in the future work section.

City Revenue Development

An interesting aspect to look at is how the revenues for the city of Zurich would develop due to the change in parking fees. Although in reality most garage parking units in the city are privately owned, we assume here that they belong to the city. While the revenues from on-street parking increased, especially due to higher prices for previously free on-street parking, the total revenue to from garage parking shrank; although demand for garage parking increased as the fees for garage parking fell. In total this resulted in an 11% decrease in revenue for the city.

5.4 Discussion and Future Work

We plan to improve and extend our work in several ways, which is outlined in this section.

5.4.1 Improvements of the Experiment

Although, the presented experiment is able to successfully demonstrate the capability of our parking model, it could be improved in the following ways.

Bigger Population Sample

To improve the quality of results, a higher population sample would be required, as artifacts do occur due to the scaling of on-street and private parking. This can happen especially for on-street parking with a low number of parking spaces. In the test scenario, a slightly too high supply of street parking is probably present due to this problem.

Adding Missing Traffic

In the demand used in this chapter, cross-border and freight traffic is missing. Adding such demand to the Zurich scenario is planned, which would not only increase traffic on roads, but also the demand for parking.

Additional Runs

For the test experiments in this chapter just single MATSim simulation runs are performed. However, in order to report the variance of simulations, several runs would need to be performed.

5.4.2 Next Steps and Future Work

In the following we outline possible directions for future work.

Mode Change

Although rising parking fees might force some people to change their travel mode, at the same time other non-car travelers might be attracted towards car usage due to the improved parking situation. Although in our simulation, mode choice was an option for the agents, no significant change in car mode was observed. Probably as a result of the slight oversupply of parking, there was little incentive for car drivers to change their travel mode to a non-car mode. However, this oversupply was also not critical enough to cause a significant shift from public transport to car traveling. Clearly it would be interesting to investigate this further in an improved Zurich scenario and a higher population sample.

Different Pricing Schemes

In the experiments there is one parking fee for the first half of the day and another for the second half of the day. The effects more frequent fee changes over the day might have, e.g. a different price every hour in the extreme case, needs to be investigated.

Additionally, the effect of prices being adapted in different ways needs investigation. In this chapter, the price is increased resp. decreased if occupancy is above resp. below 85%. In the SFpark pricing scheme, the hourly rate is raised by $0.25 if occupancy is above 80%, not changed if occupancy is in the range of 60 to 80% and reduced by $0.25 if occupancy is in the range of 30 to 60%. Furthermore, the fee is lowered by $0.5 if occupancy is less than 30%. The minimum parking price is set to $0.25. Although in this case parking fees change less often than with the pricing scheme adopted in this chapter the effect such difference in price schemes has on the stability of prices and more importantly on the overall performance of the system requires further investigation.

However, even the 85% occupancy target needs to be investigated further, as a recent paper looking at agent-based parking search in residential areas suggests that an occupancy rate higher than 85% is possible without substantially increasing search traffic (Levy et al., 2012). This is probably even more the case through the use of real-time information and mobile devices as presented in this chapter. Therefore, it seems advisable to further explore what implications a higher target occupancy rate might have on the price and utilization of parking.

The fee structure is also important, as fees cannot only be used as an instrument to influence user behavior, but can also generate revenues for the city. In the presented scenario the total revenue from parking fees for the city decreased by 11%. Regarding this, whether new parking pricing schemes can be found which maximize the income for the city while balancing supply and demand should be investigated further. The maximization of revenues for the city from parking is especially important, if such revenues are allocated to improve the situation of communities located close to the parking or used to support alternative modes of travel. This is because in this case areas with more expensive parking could still remain attractive to shoppers despite changes in price (Shoup, 2004).

Price Convergence

Another thing that is not explored in detail in this chapter is how fast prices converge. It could be useful for cities to know how long it will take before price stabilization is expected. Furthermore, the role of the initial price in this regard also needs to be considered.

Performance

More work towards the performance of the simulation is also needed. Although MATSim itself is capable of simulating millions of agents on high resolution networks (Meister et al., 2010; Waraich et al., 2009a), parking choice and search models pose additional computational burdens, so clearly this is something we need to focus on to enable the simulation of large scenarios.

Utility Function

Another aspect of parking that needs further investigation is the implementation of the random error terms within the utility function. One possible and efficient implementation of this for location choice has been proposed in Horni et al. (2011b). This might be especially useful during calibration, e.g. when real garage parking counts are different from simulated ones, either due to errors in the utility function parameters or just due to the unexplainable/random behavior of people.

Effect of Income on Walking Distance

A very important question to consider is how much effect does income have on walking distance. As briefly exemplified in the simulation section, there are factors which can render the income advantage ineffective, for example flat prices, limited parking supply, time of day, location and parking duration. Additionally, there might also be technical reasons that might have contributed to the lack of such a correlation in our experiment, e.g. oversupply of parking. A more detailed investigation of this matter is required in future.

Different Assumptions on the Knowledge and Capability of Agents

For parking selection it is assumed that the parking is reserved by the mobile device a couple of minutes/blocks before arrival. This assumption could be waived through the use of algorithms which would not reserve the most suitable parking space but instead guide the agent to that parking space. If that parking space had been occupied in the meantime, the algorithm could continue in the same way and guide the user to a different parking space. Clearly such an algorithm could improve the probability of finding a free parking space by guiding the agent to streets with several free parking spaces instead of just a single one. Although some parking search might happen due to parking which has been occupied due to the short time difference between selection of the parking and arrival, it is expected to be minimal due to the real-time information available in mobile devices.

Another investigation path could be to further reduce the capability of the drivers by assuming that some agents do not have real-time parking occupancy and/or parking price information. Although the use case for this seems to be limited due to the significance of the complex pricing structure, it would be interesting to assess how much effect knowledge or the lack of it might have on the performance of the system.

Parking Decisions

In this chapter the full capability of the Waraich et al. (2012) parking model is not described, especially its capabilities related to parking search decisions and evaluation of different parking types and their tradeoffs. We intend to work in this direction in the near future.

5.5 Conclusions

In this chapter, we applied parts of a recently proposed agent-based parking model to demonstrate that the model is capable of application in real-world parking policy scenarios and price optimization as suggested by Shoup. The model successfully captures relevant aspects of parking preferences and trade-off by people, e.g. parking cost and walk time. Furthermore, the parking model has a direct influence on other choices of the agent, e.g. mode or location choice.

As highlighted in the future work section, there are many aspects of the price optimization approach that need further investigation in addition to where the proposed model could be used. Furthermore, this chapter also lays the foundation for related work that the authors are pursuing in Waraich et al. (2013b), where the electricity demand of electric vehicles is modeled. Modeling parking decisions of electric vehicles is more complex than for gasoline vehicles, as the availability of a charging plug and the state of charge of the vehicle's battery could be an additional part of the parking decision. The agent-based aspect of the presented model seems to be a powerful approach when modeling such complex driver decisions.

Although only optimal pricing is investigated in this chapter, using the presented parking model in other contexts is also suggested in order to further our understanding of parking search traffic so that effective parking policies can be designed.

Chapter 6

Adding Electric Vehicle Modeling Capability to an Agent-based Transport Simulation

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6.1 Introduction

Battery and Plug-in Hybrid Electric Vehicles (BEV resp. PHEV) are seen by many as a key component to a future transport sector with lower greenhouse gas emissions. These vehicles do not only have a more efficient driving cycle than conventional vehicles, but also allow a diversification of energy sources for driving (MacKay, 2008). BEV and PHEV are abbreviated to electric vehicles (EV), with the exception of cases where the distinction is required.

Several governments have announced national goals regarding the number of EVs they want to have on their roads. Examples include the USA with one million EV until 2015 (White House, 2009) and Germany with the same number of vehicles until 2020 (Bundesregierung, 2009). At the time of this writing almost all major car manufacturers have either introduced a plug-in electric vehicle or are planning to do so, (see e.g. de Santiago et al., 2012).

While these numbers highlight the fact that a shift towards an era probably dominated by EVs has started, there are also many uncertainties connected with such an introduction, leading to many open questions:

Although these vehicles will require additional electricity for charging, it is not clear if the supplementary electricity can be generated in a sustainable way. Even if the required energy is coming from alternative sources, such as solar or wind power, further questions arise, such as can electricity generation match the time of electricity demand? Could the Vehicle-to-Grid (V2G) concept help in this regard, where batteries of the vehicles could act as a power reserve (Brooks, 2002; Kempton and Tomić, 2005)? Could a viable V2G model be built around ancillary services, where car batteries are used for voltage and frequency regulation (Hirst and Kirby, 1999; Kirby, 2004) and which is rewarded with a higher return than if vehicle batteries act only as power reserve (Letendre et al., 2006)? With this said however, there is a possibility that such utilization of batteries could also reduce their life span in such a way that V2G is no longer attractive (Kramer et al., 2008).

Additional questions arise around the charging infrastructure: While PHEV in the sense of all hybrid electric vehicles can both charge their batteries from the electricity network as well have a backup gasoline tank, BEV depend on a functioning charging infrastructure system. So what is the right way to provide such an infrastructure? Which are the places where such infrastructure should be built first? Will normal charging plugs or higher powered plugs allowing for faster charging prevail? Or will future cars have swappable batteries, allowing for their energy to be replenished even faster than filling up a gasoline tank (Li et al., 2011)? In addition, do new technologies for charging, such as inductive charging along roads, which charge the vehicle during the drive (Wu et al., 2011) or solar panels mounted on top of the cars have a place as part of the overall charging infrastructure (Li et al., 2009)? As vehicles with bigger battery capacity require less public charging infrastructure, could it be the case that EV with high capacity batteries might make public charging infrastructure obsolete? Or will such a mass production of large batteries never become reality? What is the best investment for public funding, e.g. subsidizing public charging infrastructure or car batteries?

There are also many open questions which arise in relation to the electricity network: While it is often suggested (Parks et al., 2007), that EVs could charge during off-peak demand during the night, there are also studies which suggest that well-meant pricing incentives could backfire and cause more damage than good, even potentially generating new peaks (Waraich et al., 2009b). They demonstrate that to solve such problems, communication technologies could be used in order to match supply and demand, in general referred to as smart charging/grid (Amin and Wollenberg, 2005). In conjunction with V2G and distributed energy generation, such technology becomes even more relevant. In this case, a building with solar panels in times of a local/temporal surplus, can feed energy into the electricity network. Furthermore, the usage of home appliances and charging of EVs could be delayed when there is an electricity shortage in the electricity network. How can such complex scenarios be modeled? While the energy increase due to electric vehicles is predicted to be small compared to the overall electricity load (Duvall et al., 2007), charging may still not be possible due to problems in the distribution network due to constraint violations at the lower level voltage network, possibly causing power line and transformer overloads (Farmer et al., 2010). How can such possible bottlenecks in the electricity network be uncovered to allow owners of the electricity network to prepare for possible future EV scenarios?

In order to study these questions, models of the electricity demand introduced by these EVs, including preferences of the drivers/owners are required, which are coupled with electricity supply models. Supply models refer to electricity network flow models, but can also include intelligent controls for matching demand and supply and electricity generation. Discussing related work in the background section, we argue that there is a lack of microscopic models related to EVs, which could help in the analysis of these problems at an adequate level of detail. Indeed, this is essential when studying where in the distribution network transformer overloading and other problems occur, such as those described in Farmer et al. (2010). In this regard, reusability plays an important role, as building complex models from scratch is a difficult task.

Based on the authors' previous work related to detailed demand and supply modeling of EVs within an interdisciplinary working environment, in this chapter a framework for EV modeling is presented. Key features of the framework include that it is open source and as such allows not only free access to its use in other projects, but also spurs contribution of new modules, so that the wider EV research community can benefit from it. According to the best of the authors' knowledge, this is the first open-source framework supporting detailed EV demand modeling with interfaces for integration with supply models.

The rest of the chapter is structured in the following way: In the next section related work is discussed, following which the framework itself is presented, as is a case study for the city of Zurich, which exemplifies the potential application of the framework. After discussing different aspects of the case study in relation to the framework, future work is outlined. Following the conclusions, at the end of the chapter a further reading list is provided.

6.2 Background

6.2.1 The Big Picture

There are numerous studies related to electric vehicles, many of which look at different countries, regions or cities, e.g. Vermont in Farmer et al. (2010) or British Columbia in Kelley et al. (2009). Some studies are based on surveys (Axsen et al., 2009), others on simulations (Knapen et al., 2012), and others look at different types of charging (Lopes et al., 2009) or placement of charging stations (Chen et al., 2013). Due to space constraints it is not possible to discuss all of the literature here. However, if one focuses solely on those contributions trying to assess the impact of EV charging on the electricity network, one can categorize the papers according to the level of detail with which they model demand and supply. The first category of papers is only concerned with an aggregate view of the problem (Hadley and Tsvetkova, 2009; Wynne, 2009). Whilst such papers do not try to model the demand and supply in much detail, they do provide system wide key figures, e.g. total energy consumption. It is clear that although such work is helpful in order to get an overview on aggregate energy demand and CO_2

reductions, it is not able to assess exactly where in the electricity network problems might occur due to the introduction of EVs. Many such studies implicitly assume that the electricity network will be able to handle the extra load, which does not take existing power line and transformer constraints into account, as for example pointed out by Farmer et al. (2010).

When starting to refine the models, there are two strands of work, where people either try to refine the models of demand or supply side. While only few electricity demand models exist which could potentially provide detailed demand side modeling, e.g. Knapen et al. (2012), on the electricity network side, many detailed supply models are available for investigating the impact which EVs have on the distribution network (e.g. see Lopes et al., 2009).

The research gap of detailed electricity demand and supply modeling is recognized also in a recent literature review assessing the impact of PHEV on the distribution network (Green II, 2011), where the authors' first conceptual paper on this issue is strongly endorsed (Galus et al., 2009). While it is clear that the problem at hand does require detailed modeling of demand and supply side, most studies leave one out. It is the authors' contention that several reasons lie behind the scarcity of detailed modeling of both sides of the issue. These reasons will be pointed out in the following sections when comparing related work.

6.2.2 Related Work

As previously mentioned, many studies look at different charging schemes, vehicle-to-grid, etc. although the focus is often on aggregates. In the following three pieces of work provide a good sample of the current state of the art in this field. After discussing the work briefly, we will highlight why we think that there is a possible a gap between the requirements of the problem at hand in terms of resolution and detail and why this is still missing.

Binding and Sundstroem (2011) attempted to model both the demand and supply side of the electricity network. This includes, among others, a travel demand model and an electricity network model. The paper focuses on integration of both demand and supply and mostly stresses the performance of the simulation. The modeling of the traffic is carried out in an event-based fashion. For modeling activity and trip durations and departure times, certain distributions are used, e.g. normal and uniform distribution. Although an agent-based approach is used, there is no special emphasis on modeling of individual preferences of people or households. When making comparisons to the authors' previous work (Galus et al., 2009), they argue in favor of a fully integrated approach of the transportation and power system simulation, in order to avoid performance overheads. This point is addressed later in the present chapter.

Cui et al. (2012), is also based on an agent-based approach. Their study area is Knox County, TN, which is divided into geographical zones of around 6 square kilometers. An agent-based modeling environment called NetLogo is used to model people (Tisue and Wilensky, 2004). A vehicle ownership model is estimated based on Nested Multinomial Logit whilst they also take taste heterogeneity of different households into account. With regards to charging, they assume that people will start charging immediately, when arriving at work and back home. The level of detail of the transport model is not described in the paper, but as the charging profiles at work and home are identical, one can infer that the work duration is probably the same for all agents. This results in a repetition of the exact charging pattern at work in the morning and home in the evening.

One of the most sophisticated models for EV demand modeling is presented in Knapen et al. (2012), where the electric power demand by EVs is modeled for the region of Flanders. They use the FEATHERS (Bellemans et al., 2010) activity-based model to predict the daily schedules of people. This involves a microscopic level demand modeling and route assignment. Through simulations four different kinds of charging strategies are evaluated on an aggregated level. The average zone size in the case study is 13 square kilometers.

These three papers are among the most detailed in terms of EV demand modeling. However, from the point of view of the electricity network, more detailed demand modeling is required. For example, in the case study for the city of Zurich presented later in this chapter, each electric node covers, on average, an area of 150-200m radius. This means that in order to appropriately analyze the electricity network with regards to possible future EV charging, one must perform far more detailed and higher resolution simulations than is the case in these three papers. But why is electricity demand side modeling still happening aggregated on a system wide level? The authors think there are several reasons for this, making it a very difficult problem to solve:

The first hurdle towards a detailed demand and supply side modeling is that only an interdisciplinary approach including for example, the competences of transportation, electrical engineers, computer scientists, mechanical engineers, etc. can handle such a project. However, even if a team is able to master this hurdle, it does not necessarily mean that the EV related study has the goal of detailed modeling in mind. Furthermore, most studies focus on a specific study area. As such, it is difficult for different scientists to apply these models in other regions, as the implementation and detailed documentation of the models is often not publically available. Furthermore, as the models are often implemented for specific studies, they are not designed with extension in mind, rendering their reuse and extension difficult. It therefore seems that most studies related to EV start from scratch, although similar studies have been conducted previously.

The authors of this chapter have gone through most of the steps described above: Starting with an interdisciplinary team of transportation-, electrical-, computer science- and mechanical engineers a detailed simulation of the city of Zurich is performed, both of the demand and supply side. In this chapter it is tried to fill the gap in the research community described above. Starting with detailed demand modeling, it is tried to generalize the authors' previous work, such that other EV researchers can possibly reuse it. Furthermore, effort is made towards publishing the work open source with documentation, thus making it possible for others to access this work. By doing so, we not only hope to vitalize detailed EV demand modeling, but also hope that some researchers will follow this practice and contribute their work, such that the whole EV research community can benefit from it.

In the following some of our preceding work with regards to the EV framework is described, before describing the framework itself.

6.2.3 Preceding Work

Galus et al., (2009) presented for the first time, the concept that one could bring together detailed demand and supply side modeling by integrating transportation and power system simulation models. Furthermore it showed that these models could be run iteratively. The idea is that electricity could be priced with a location dependent virtual price signal using an agent-based approach, and agents could adjust their demand accordingly, such that demand and supply could be matched (Galus, 2012).

Such a test system was implemented and presented in Waraich et al. (2009b), and Galus et al., (2012b), where different scenarios are simulated including uncontrolled charging, time of use pricing and centralized smart charging. In case of smart charging a central aggregator in the system communicates to the vehicles, when they should charge, while taking inputs like parking duration, state of charge and planned trip distance into account. It successfully demonstrated that from different starting system conditions the prices do converge to a stable state, such that all vehicles can be charged. Furthermore, the simulations also show how pricing could affect the behavior of people.

These models have been further developed further, as presented in Galus et al. (2012b), where a detailed vehicle fleet (Noembrini, 2009) and an energy consumption model (Georges, 2012) is added. In the meantime, work on the demand side modeling has been extended and generalized further as a framework. Whilst some elements of the framework have been presented in the papers mentioned above, here the whole framework and its modules are presented for the first time including an application.

6.3 The Transportation Energy Simulation Framework

6.3.1 Requirements and Reasoning behind the Framework

Before describing the Transportation Energy Simulation (TES) framework itself, the general requirements of the framework are outlined.

The framework needs to cover a wide range of applications as presented in the introduction. This means that the framework should be built modular and extendible. With such a framework, people could plug together complex scenarios themselves, e.g. by looking at the examples provided, extending simpler models and implementing new models using standardized interfaces. Furthermore, it should be possible to implement a model inside or outside the framework. This enhances the flexibility of the framework because not all libraries and tools required for an application might be available through the framework and full integration might require too much time.

A second important requirement for the framework is that one should be able to model change in behavior at a person level. It should be possible to infer how people might possibly change their behavior due to certain policy measures, e.g. change of prices or resource availability, such as charging stations, etc. Furthermore, certain applications also require that one is also able to model preferences of individuals, for which the input can for example stem from stated preference surveys (Weis et al., 2012). Therefore, it is a requirement for the framework that people are modeled individually as agents taking decisions rather than an aggregated group.

As electricity demand by EVs is generated by people's travel demands, a transport model is needed which supports detailed spatial and temporal modeling such as MATSim (2013). Furthermore, the performance of such a traffic simulation is also important as one wants to be able to capture the whole daily movement of possibly millions of agents throughout the whole day.

In order for the system to be beneficial to a wider audience, it is important that the system is not only available for free, but also that the system is open source. This would be in line with the peer review process often adapted in research, so that not only the description of models can be reviewed, but also the implementations themselves.

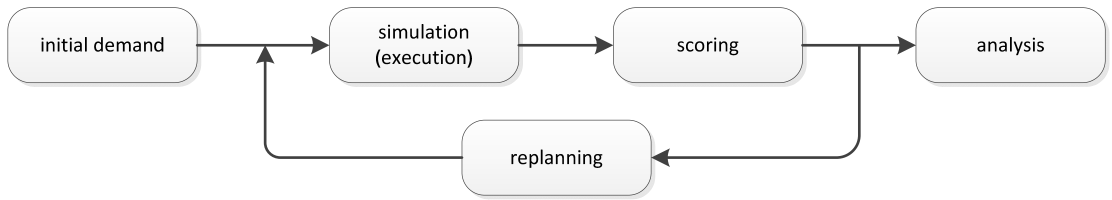
The last requirement is probably the most important when it comes to the success of such a framework and has to do with the usability of the framework. Documentation, examples and tutorials should be available to support people and make the initial learning as simple as possible. In addition the availability of visualization tools for the simulations can facilitate the work with the framework. Although from a scientific point of view one might pay the least amount of attention to this requirement, it may well be the single most important requirement for the actual adaptation of such a framework, especially by those who are new to the field.

As mentioned earlier, the framework presented is a continuation of previous work, which uses an agent-based travel demand and traffic simulation called MATSim. In the following section the MATSim simulation is briefly described, before characterizing the TES framework and its interaction with MATSim.

6.3.2 MATSim

Figure 6.1 shows MATSim's simulation process: Each agent in MATSim has a daily plan of trips and activities, such as going to work, school or shopping. The initial daily plans of agents are provided as input in the initial demand step together with supply models, e.g. street network and building facilities. These initial plans can be based on, for example, activity/travel diaries of people. The goal of the MATSim simulation process is to optimize the plan for each agent while respecting supply side constraints and the preferences of each agent. The plans of all agents are executed by a micro-simulation, resulting in traffic flows along network roads, which can cause traffic congestion. The execution of these plans is then scored and assigned a utility value. For example, a person with lower travel time has a higher utility than one who has a longer congested travel time. Additionally, working and other activities increase the utility. The goal of each agent is to maximize the utility of its daily plan by *replanning* it after each iteration, e.g. changing routes, working time, travel mode or location choice. In this step, either a new plan is assigned to an agent by adapting a previously executed plan, or a previously executed plan is reselected. Plans with a higher score have a higher chance of reselection, while plans with a lower score are deleted over time, as only a limited number of plans per agent are kept. This idea corresponds conceptually to mutation, selection and survival of the fittest in a co-evolutionary algorithm (Holland, 1992). This iterative process approaches a point of rest corresponding to a user equilibrium called relaxed/optimized demand.

Figure 6.1 Co-evolutionary simulation process of MATSim



6.3.3 TES Integration with MATSim

Next the interaction and integration between the TES framework and MATSim is described. The development is facilitated by the fact that MATSim itself is built in a modular fashion and as such facilitates extension. Thus, at many points in the MATSim simulation, it is possible to provide additional functionality, and as such to extend the overall simulation. This allowed the development of the framework, without having to change any of the code of MATSim itself.

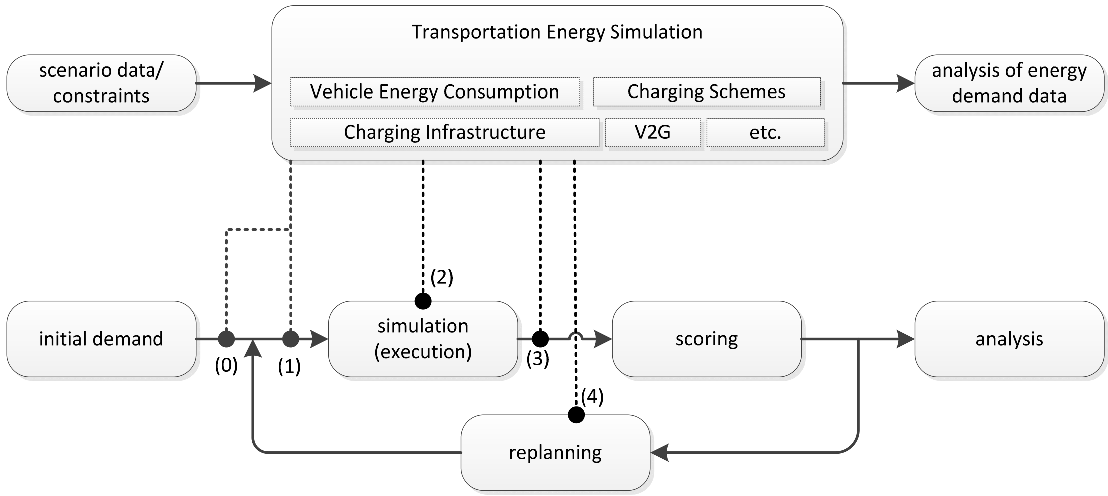
Figure 6.2 shows how TES is plugged into MATSim. TES itself consists of several modules, which are needed for simulation of EV related scenarios, such as energy consumption or charging modules. These modules can be setup according to scenario specific constraints, before starting the TES simulation. When TES is started up, it plugs itself into MATSim at several points before the combined MATSim-TES simulation is performed itself. Although the modules are described in detail later, here a brief description of the different plug-in points between MATSim and TES is provided:

(0): This refers to the point in time, where MATSim has just been initialized. At this time TES can perform operations required for initialization of the simulation, such as defining at which locations parking charging infrastructure is available.

(1): This refers to the time just before a new iteration in MATSim is started. This is already part of the MATSim iteration loop. Here, operations, which are part of the optimization can take place, e.g. a policy change. For example, if charging stations need to be priced according to demand, the price can be adapted here.

(2): During the execution of the MATSim simulation, TES can extend agent and vehicle models. For example, the energy consumption of vehicles moving along roads can be updated or vehicles can be charged according to the preferences of the agent/charging schemes.

Figure 6.2 An overview depicting the Transportation Energy Simulation Framework and MATSim together with important integration points



(3): This point indicates the time when the micro-simulation execution in MATSim is over, and can be used to produce statistics of the iteration or for adapting the utility score of the agent. For example, the cost of charging can be aggregated and added to the utility score of the agent, so that the prices does influence the decision of the agent in future iterations.

(4): The plan of the agent can be adapted during the replanning step in MATSim as explained earlier. This can also be utilized to adapt choices in the context of EVs. For example, if the assignment of vehicles to people is not fixed, a vehicle owner could change the vehicle type to maximize its utility. In this case, people with easier access to charging stations might prefer EVs, while others might prefer PHEVs or switch to a different mode.

6.3.4 Modules

After providing an overview regarding how TES is integrated into MATSim above, this section describes the individual modules and features of the framework in more detail.

Vehicle Characteristics and Energy Consumption

At the time when the first simulations involving TES modules were presented, see (Waraich et al., 2009b), MATSim did not have any model to distinguish different types of vehicles. Therefore, a new system for modeling vehicle types was developed. The idea behind the modeling of vehicle type in TES is such that one can quickly switch together any type of EV. For example, one can plug together a vehicle, which supports charging at stationary plugs and has a swappable battery or can perform inductive charging along roads. A solar roof module for addition to EVs is work in progress.

In addition to different types of charging options, each vehicle also has an energy model attached. It defines how much energy that vehicle consumes during driving. The energy consumption depends e.g. on the weight and the power of the vehicle. While energy consumption models for certain vehicle types are available (e.g. Abedin, 2012; Georges, 2012), an interface is provided to import new energy consumption models according to the needs of specific case studies.

While for the energy consumption of conventional vehicles (using gasoline, diesel, hydrogen, bio-diesel, etc.) just their energy consumption is logged for later analysis as they drive, for EVs the energy consumption is modeled in more detail. For such vehicles a battery capacity needs to be defined, for which the state of charge (SOC) is updated during driving and when charging. The PHEV model, which is implemented at the time of this writing, is a series hybrid (Chan, 2007). Such vehicles use the electric drive as long as the SOC is above a minimum threshold value which is determined by battery life time considerations (e.g. 20%). Thereafter, the onboard electric generator is turned on to run the vehicle in charge sustaining mode using gasoline. This means that, on average, over a driving cycle the battery is not charged in this mode. Such vehicles have one energy consumption model for the electric drive and a second one when the on board generator is turned on. More complicated energy control strategies for PHEVs, such as those presented by Tulpule et al. (2009), can be created by implementing the application programming interfaces provided in TES in this regard.

After defining a vehicle together with its energy consumption model, the vehicle needs to be assigned to a vehicle owner. This assignment can be static or dynamic. In the first case the assignment is conducted once in the simulation and is not changed thereafter. Dynamic assignment of vehicles means that the vehicle used by an agent can change over iterations. The latter is not implemented hear, for more information see the discussion and future work section.

As briefly mentioned in the previous section the energy consumption update is performed during the micro-simulation. This means that the SOC of the batteries is updated as the vehicle is traveling over each road segment. Moreover, during the micro-simulation the charging of these vehicles is performed, using a charging infrastructure. This is described in the next section.

Charging Infrastructure

Several charging infrastructure modules are available, and their location and configuration, such as plug availability, can be defined during the initialization of the simulation. Furthermore, to facilitate a simple scenario setup, one can also easily deploy a charging infrastructure according to activity type. For example, one can define that charging is available at home with 3.5 kW and work with 11 kW.

Besides modules for plug-in charging infrastructure, a module for inductive charging has also been implemented. Vehicles equipped with such modules can charge as they drive along roads, where the corresponding technology is installed. In the first tests, which were performed using the inductive charging module (Abedin and Waraich, 2013), only one type of power is available to all vehicles. This is currently being extended, such that differences in charging capability of different vehicles can be accounted for, as described in Suh et al. (2011).

At the time of this writing, a module for optimal placement of charging stations is still work in progress. To exemplify optimal placement of charging stations, at least one application of this is planned to be available in the initial version of the framework for reference. As swapping stations and dedicated public fast charging stations are also of interest to the EV research community, ongoing work is providing interfaces and basic implementations of such modules.

Charging Schemes

A charging infrastructure alone, as defined in the previous section, is not sufficient to capture the variety of cases and scenarios, outlined in the introduction. Therefore, the simulation of the charging infrastructure and charging behavior of vehicles is controlled by so called charging scheme modules. There are several charging schemes which are available at the time of this writing in TES, although new ones are being developed.

One of the charging schemes available for stationary charging is known as uncontrolled charging (sometimes also referred to as dumb charging). It implements the simple behavior that an agent just plugs-in the vehicle whenever a charging plug is available and starts charging immediately. Such a module is implemented in TES by tracking the agent during the MATSim simulation and charging the vehicle when the vehicle arrives at a parking place where an electric plug is available.

A second charging behavior for stationary charging is available for scenarios where the price for charging changes over the day. These prices can either be fixed for the whole day in advance or vary throughout the day. A vehicle charging controller can be added to a vehicle, and it can charge the vehicle according to the desires of the agent. E.g. by specifying the time, when charging should start, which corresponds to technology already available. One such charging module is already implemented into TES. It handles the case where charging prices are known to the vehicle for the whole day. In this case, the agent tries to minimize the charging price it needs to pay while considering temporal and spatial variation of prices. This also takes planned trip throughout the day into account. If required by the investigated case study, this charging price can also be integrated into the overall utility function of the agent, such that it has direct influence on the behavior of the agent and its various travel related choices, as presented in Waraich et al. (2009b).

As indicated in the background section, charging modules which allow for smart charging are also available in TES. Such a module can be integrated with an external power system simulation, as demonstrated in Waraich et al. (2009b). In this case it is tried to charge all vehicles, while taking electricity network constraints into account. Whereas the smart charging approach used in Waraich et al. (2009b) is based on a central entity, which controls the charging behavior of vehicles connected to the electricity network, a decentralized approach is tested in Schieffer (2010) using TES. In this case a charging module is implemented which assumes that all vehicles are provided information about the base load distribution curve and can decide independently from a central entity when to charge while trying to act in the best interest of the electricity network owner. Although it is not always possible to make the assumption that car owners would act in the best interests of the electricity network, which is possibly in conflict with their own interests, it provides a starting point for further research in this direction.

For inductive charging, at the moment only a default charging scheme is implemented, where vehicles just try to charge whenever inductive technology at roads is available. More advanced inductive charging schemes could include charging price optimization for the agent. Policies of the electricity network could also be included in some charging schemes, e.g. the inductive charging capability of a road could be turned off to shed load.

Vehicle-To-Grid (V2G)

In Galus and Andersson (2011), an early version of TES is utilized in combination with an intelligent controller for PHEV storage management. It is shown that such an approach could be utilized to balance the fluctuations in energy generation from renewable energy sources such as a wind park. In this approach only the output from the TES framework is utilized. The first integrated simulation of V2G inside TES is presented in Schieffer (2011). As this is still preliminary work for integration of V2G modules into TES, there remains a great deal of potential when it comes to extension of the framework in this regard.

Output Modules

As during the simulation all energy consumption and EV battery SOC updates are logged, it is possible to easily perform various kinds of analysis, e.g. for CO_2 emissions. Furthermore, simple graphs can also be generated, automatically summarizing results after each MATSim iteration or at the end of the simulation.

Although custom analysis outputs can be built by using interfaces provided by TES, there is still a big gap in terms of visualization of the TES simulation. While free and commercial visualization of the MATSim simulation are available (MATSim, 2013), those visualizers are not built with support of EV related scenarios in mind. Such visualizations could not only expedite the learning process of the framework, but also help during the implementation of new modules and debugging.

Adding Modules

Modules can interact with TES in two ways, either as modules, which are implemented inside the framework, or as external modules. While modules in TES need to be implemented in Java, communication to outside modules must happen through interfaces. If outside modules only provide input to

TES or need the output from TES at the end of the simulation, the data exchange can happen through files. But if an external module needs to be invoked after each iteration, it is best to automate the invocation of the external module, for which examples are provided with TES. Alternatively, if an external module needs to be invoked even more often, e.g. during the simulation itself, it might be advisable to re-implement such modules inside TES, as this might otherwise lead to high overheads and performance degradation, in turn leading to long run times, especially for larger scenarios.

Performance

As TES aims to be able to simulate large scenarios, with possibly millions of agents on high resolution navigation networks with millions of road segments, the performance of the simulation is very important. MATSim itself is capable of simulating such large scenarios, as demonstrated by Meister et al. (2010). This is achieved by utilizing multiple cores/processors for the micro-simulation (Dobler and Axhausen, 2011).

As TES requires many operations, which must be performed while following the agent throughout the simulation, the handling of events generated by the agent throughout the simulation needs to be fast. This has been implemented by using the concept of parallel event handling (Waraich et al., 2009a), which allows TES modules which are related to, for example, SOC management to be handled in parallel with the micro-simulation execution. This means that all presented TES modules are fully integrated within the MATSim simulation.

Modules Contributed by other Researchers

Although the framework is not yet available publicly (planned for the end of 2013), several researchers have already contributed to its implementation besides the first author. Indeed, Abedin (2012) contributed through an energy consumption model for electric vehicles, which is based on Faria et al. (2012). Furthermore, Georges (2012) contributed with energy consumption models for small VW Golf sized vehicles, with conventional, plug-in hybrid and electric vehicle powertrains. While the model implemented by Abedin (2012) just takes the speed driven into account, the second model also takes traffic conditions into account, which is described as part of the case study later in this chapter.

Planned Modules

There are several modules for which a reference implementation is planned. Such a basic or default implementation can help to prepare the appropriate interaction and integration with other modules and other researchers can simply extend the work or re-implement modules based on clearly defined interfaces. There are several modules which are planned or which are a work in progress, such as optimization of charging station locations, a solar panel module, electricity model for buildings and adaptation of routes of agents due to swapping of batteries or performing fast charging. Such planned modules and work in progress is described further in the future work section.

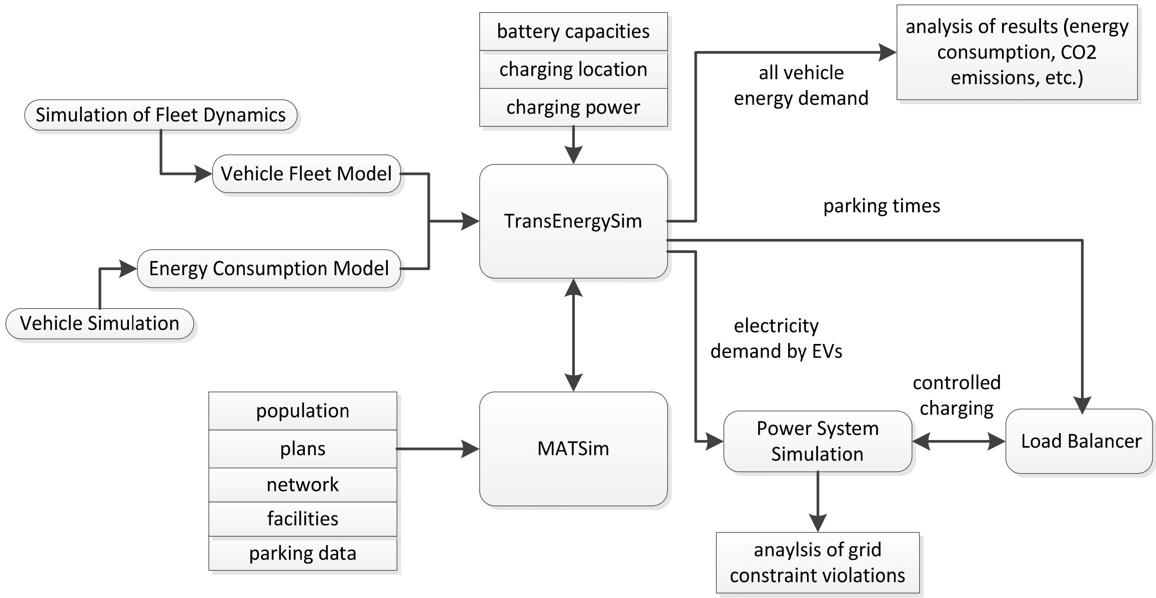
After the presentation of the TES framework in this section, which is rather abstract, the next section presents an application of the framework in order to allow the reader to develop a better understanding of how some of the modules of the framework can be utilized in practice.

6.4 Case Study: City of Zurich

In this section the ARTEMIS case study for the city of Zurich is presented (Galus, Georges and Waraich, 2012), which investigates the possible impact of future EV scenarios on the electricity network of the city. The TES framework is used in conjunction with several embedded models and external modules. The interaction between the different modules and sub systems involved in the simulations is depicted in Figure 6.3. For the simulation several inputs are required for TES and MATSim. For TES, scenario specific information regarding the vehicle fleet and its energy consumption is provided as input. This is further described in the sections *Fleet Dynamics*, *Vehicle Energy Consumption Model* and *Scenario Overview*. For MATSim also scenario specific inputs are provided, which are described in the *Traffic Simulation Model* section. In addition, extensive information on the electricity network is needed, with is further described in the section entitled *Power System Simulation and Load Balancing*.

There are three outputs from TES, which are analyzed further: A) The spatial and temporal distribution of the energy consumption for overall energy consumption and CO_2 emissions analysis. The latter is further described in the results section. B) The electricity demand by EVs which is given to the power systems simulation as input to determine whether the required demand could be supplied by the electricity network. C) Information on EV parking times given as input to the load balancer to handle cases, where electricity network constraint violations occur. In such cases controlled charging is applied to possibly solve the problems. This is further described in the section entitled *Power System Simulation and Load Balancing*. Before presenting the experimental results, more details on the integration of the modules into TES are described.

Figure 6.3 Interaction of the Transportation Energy Simulation framework with MATSim and external models within the case study of the city of Zurich. External models include the Vehicle Fleet, Energy Consumption and the Power System Simulation.



6.4.1 Fleet Dynamics

By fleet dynamics the temporal change of the fleet composition is meant. The existing fleet is a heterogeneous mixture of all kinds of vehicle classes, shapes and propulsion technologies. Indeed, these amount to far too many individual designs to be modeled and simulated. This complexity is reduced by parameterizing the fleet and modeling it as a composition of different vehicle types, which are described by four properties: The powertrain (conventional vehicle, full-hybrid, PHEV, BEV), the fuel used (gasoline, electric), the vehicle's power (eight categories, with most of them ranging between 50 kW and 200 kW) and the vehicle's mass (ten categories considered, most of which range between 900 kg and 2600 kg). This means that in total 320 types of vehicles are considered in the simulation. Furthermore, for modeling future years, it is considered that each year a certain number of vehicle owners change their vehicle, new people start driving and others quit using a car. Furthermore, the technology of the vehicles also changes over time. In the following it is briefly described, how considering several boundary conditions, the fleet composition of the reference years 2020, 2035 and 2050 are approximated.

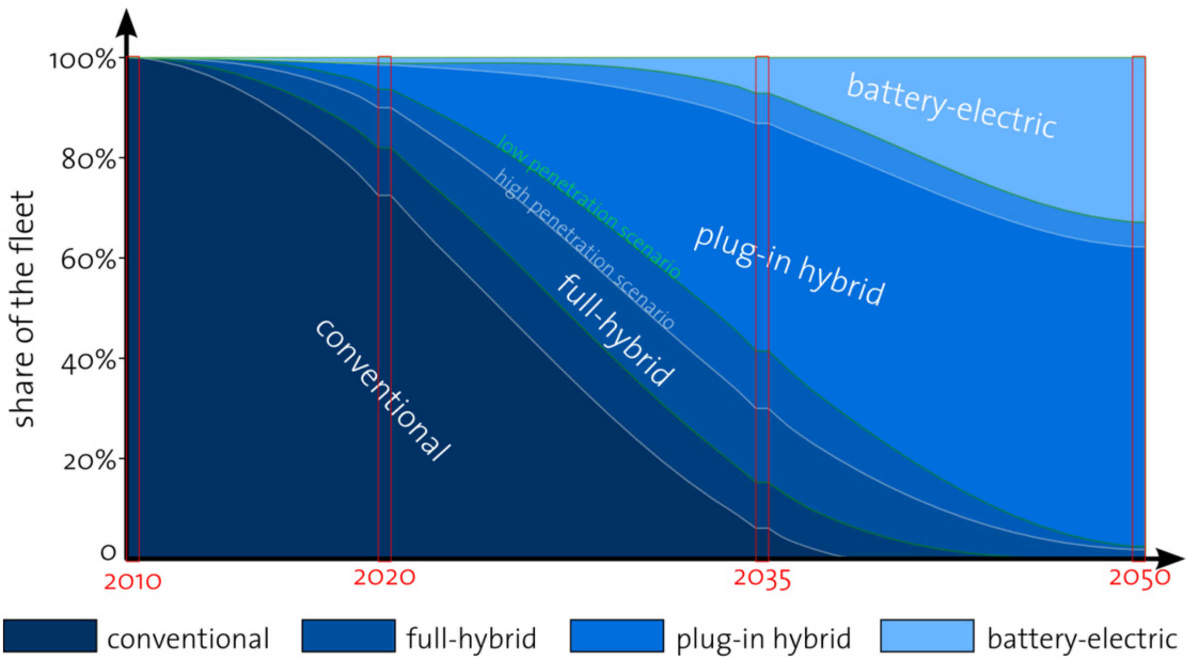
Based on the Swiss federal statistics for the reference year 2010, all registered vehicles are mapped to vehicle classes according to the four vehicle properties described above. The dynamics of the fleet within a single vehicle class is modeled according to Noembrini (2009). It is assumed that certain vehicle models are renewed on an annual basis. The probability of such a change depends on the age of the vehicle. In general, the removal probability of a vehicle increases until a certain age, after which this probability drops back to zero, modeling the case that a vehicle becomes an oldtimer.

In order to perform the simulation for the surroundings of the city of Zurich, the federal statistics for the vehicle types of all of Switzerland are used, as the data for the study area alone did not contain all the vehicle properties required. It is assumed that the vehicles considered have a similar mass and power distribution to that of the Swiss-wide federal statistics. As the study area covers around 20% of the overall Swiss population, with people from both urban and suburban locations, this assumption seems appropriate. The number of vehicles in each category defined by the four previously mentioned properties is based on a linear vehicle class penetration model based on the fleet characteristics from Bundesamt für Statistik (2013).

For simplicity's sake the possible growth over time of the electricity network, road network and population growth predictions are ignored and instead the data from the year 2010 is used. This means this study looks at the impact on the current electricity network based on scenarios, with increasing EV and PHEV penetration. This in turn means that the overall size of the fleet in all scenarios remains the same. The implications of this simplification and current efforts for improvement are examined further in the discussion section.

It is assumed for all scenarios that over time the market share of vehicles with regards to mass and power distribution does not change. Of course the drive technology available in the market changes as full-hybrid, PHEV and BEV enter the market replacing conventional vehicles. The probability of a drive technology change is based on the market share of EVs in 2050 according to ewz (2009), where two scenarios are distinguished with a lower and higher market penetration of BEV. Based on these scenarios, a low-EV and high-EV penetration scenario is defined, (see Figure 6.4).

Figure 6.4 Market share of low-EV and high-EV penetration scenarios from 2010 to 2050 in comparison.



The low- and high-EV scenarios are distinguished through the use of different colored lines. The white lines show the scenario, where EVs replace the conventional vehicles faster from the market (high penetration scenario), while the green line shows the scenario, where conventional vehicles are replaced from the market at a slightly slower rate (low penetration scenario)

In the low-EV penetration scenario, it is assumed that as of 2035 all conventional vehicles will have been replaced in the market by full hybrids or EVs. From 2040 onwards, even full-hybrids are replaced over time by PHEVs and BEVs. In the high-EV penetration scenario, an environment favoring EV penetration compared to the low-EV scenario is assumed and as such the BEV market share increases faster over time. Factors which could induce such an EV friendly development are faster development of battery technology, faster and ubiquitous availability of charging infrastructure, and PHEVs becoming available everywhere in the market between 2015 and 2020. Indeed, from 2015 onwards no new conventional vehicles are released into the market.

While one of these scenarios is called low-EV penetration and one high-EV penetration, this does not indicate that these scenarios mark lower or upper bound for electrified vehicle penetration. On the contrary, such naming is merely meant as a distinction between the two scenarios.

6.4.2 Energy Consumption Model

After describing the vehicle fleet dynamics, in this section the energy consumption models of the vehicles are characterized. The models are pre-calculated externally and then integrated into TES, as a real-time model calculation would require a lot of time, thus affecting simulation performance. The data exchange to TES is via a regression model, which allows us to calculate the energy consumption of each vehicle based on approximated traffic patterns and the technical specification of the vehicle.

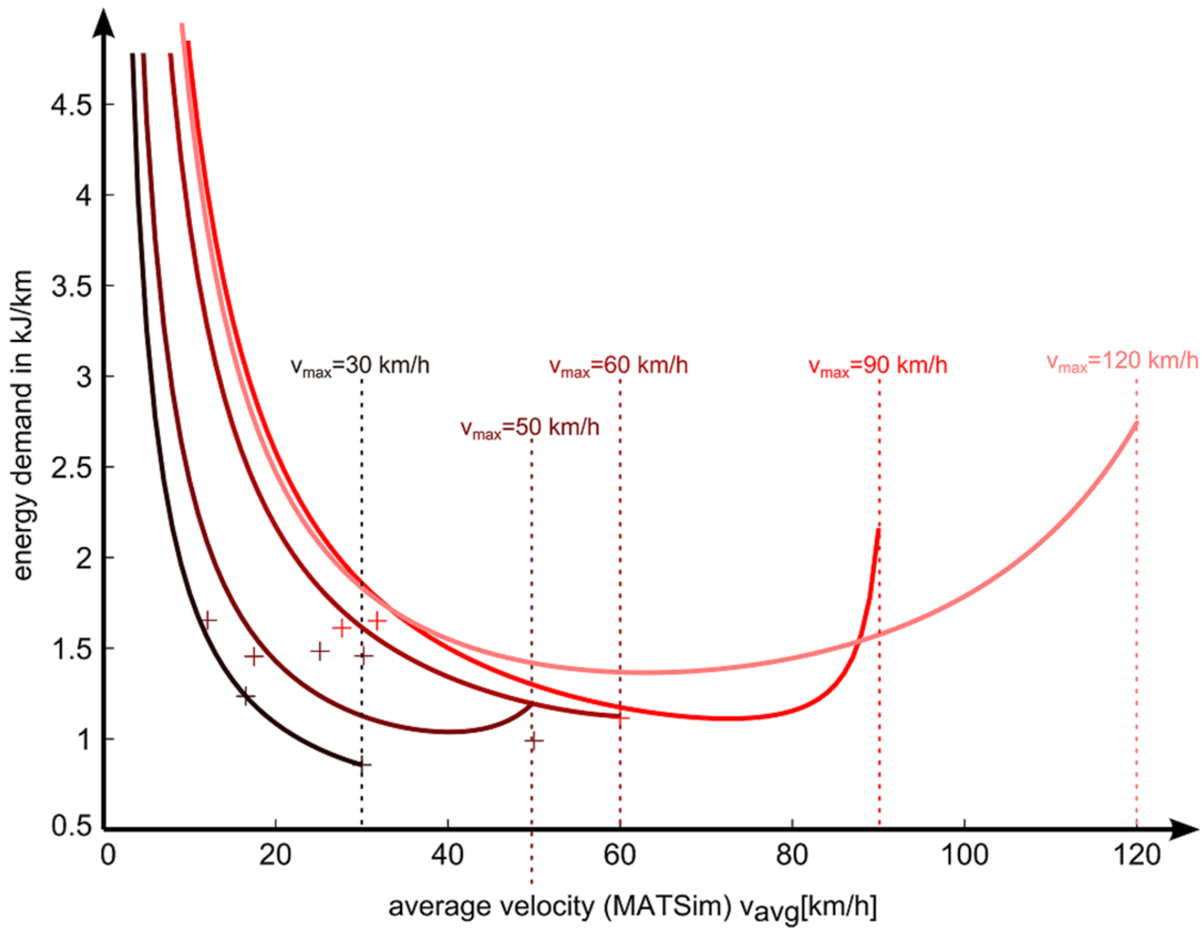
Modeling energy consumption, while considering driving patterns is quite complex. Even on a free road the vehicle speed is mostly not constant, e.g. due to curves. In addition, speed fluctuations due to interaction with other traffic participants are even stronger. In order to prepare a vehicle energy consumption model, which is suitable for usage in TES, a regression is formulated, which allows to calculate the energy demand of a vehicle based on the maximum allowed driving speed on the road and the average speed driven by the vehicle. Such a simplification is needed, as the simulation within a road in the MATSim micro-simulation is not detailed enough to capture second-to-second driving patterns. However, as an unlimited number of driving profiles can lead to the same average driving speed, a driving cycle, which is based on data from European cities is adopted (André, 2004).

For each vehicle, in addition to the four vehicle properties (power train, fuel, power and mass) other parameters are considered also, such as aerodynamics, rolling resistance, gravity and inertial forces. After calculation of the forces involved, a detailed computer simulation of each vehicle type is performed, including modeling of their motors and energy conversion. Due to space constraints, it is not possible to describe the mathematical formulation of the models of the different vehicle types here. More details can be found in Georges (2012).

In order to also account for technological improvement over time of the various vehicle types, an annual energy demand reduction, which differs for each vehicle power train, is used, following the model described in Safarianova et al. (2010). This model makes the assumption that electric vehicles have less potential to improve their energy economy than conventional vehicles, as electric vehicles are already far more efficient than conventional vehicles.

A sample regression model for a compact car is shown in Figure 6.5. It shows for five road types with different speed limits the energy consumption depending on the average speed driven.

Figure 6.5 Energy regression model for a compact car with a conventional powertrain for the year 2012.



Each line represents one discrete legal speed limit. The crosses indicate the raw-data obtained by simulation.

6.4.3 Travel Demand and Traffic Simulation Model

After describing the vehicle fleet and energy consumption models, which are inputs for TES, this section describes the inputs for the MATSim simulation. Although the study area for the electricity network is only the city of Zurich, the travel and traffic simulation model contains all agents residing within 30km around a central place in Zurich (Quai Bridge). Additionally, such agents, who reside outside this 30km circle at any time of the day, are also included in the scenario. The reason for not only modeling the city of Zurich is that many of the agents working in Zurich live outside of Zurich and therefore influence the electricity demand in the city when considering EVs. Furthermore if only agents residing in the city of Zurich are modeled, much of the traffic interactions between different participants of the road network would be missing.

The MATSim demand model used in this case study is based on a scenario of Switzerland presented in Meister et al. (2010). In this scenario, a detailed navigation road network with over one million road segments is used. Such a detailed network is essential for uncovering electricity network constraints, which are only visible at the lower layers of the distribution network. A detailed description of the generation of initial plans of the agents' is omitted here, as this is not part of the work in this case study and is presented in Meister et al. (2010). In general, the generation of these initial plans can be based on activity/travel diary data, using activity-based models of travel behavior, such as those presented by Arentze and Timmermans (2000). In addition to travel diaries, other data sources, such as GPS tracking data (Schüssler and Axhausen, 2011) or data from public transport fare cards (Lee et al., 2012) can also be utilized.

Due to the large number of scenarios and time constraints of the study, only a 10% population sample is used with around 180 000 agents. Such population sampling is common practice, where the network flow capacities and that of the infrastructure (e.g. parking) are adapted accordingly to match the sample size.

Whereas parking is often neglected in traffic simulations, e.g. in Meister et al. (2010), initial investigations towards electric demand modeling within this case study showed that this would not render results which are suitable for the detailed study at hand. If the simulation is executed without detailed information on parking, this can result in a higher demand for parking than the actual supply. This means that although in reality, an area with low parking supply would not be attractive for travel with a car, it might be attractive in the simulation, if parking supply constraints are not modeled. This problem is solved using the parking choice model presented in Waraich and Axhausen (2012b), where all 300 000 parking spaces including private parking, street parking and garage parking in the city of Zurich are modeled.

The modes of transportation available in this simulation are car, public transport, bike and walk. Only car driving is simulated physically, taking road capacity and space constraints into account. The travel times of the other modes are based on simpler models, such as average speed for bike and walk and fixed travel time matrices for public transport. The agents in the traffic simulation have the freedom to change travel mode, departure time, activity duration and route. 50 iterations of the traffic simulation are performed in order to reach a near-relaxed state.

6.4.4 Power System Simulation and Load Balancing

After the description of major inputs to TES and MATSim this section describes how the electricity demand output for the electric vehicles determined by TES is evaluated in the power system simulation to investigate possible electricity network constraint violations. Furthermore, the load balancer is described. It is attached to the power system simulation and can perform controlled charging, meaning that it can redistribute power demand of vehicles to avoid electricity network constraint violations.

As mentioned earlier, one of the main objectives of the case study is to establish whether or not EV charging could violate physical constraints of power lines and transformers in the electricity network in Zurich. The electricity network model which is used for such analysis is provided by the utility company of Zurich (*ewz*). The electricity network model is structured into network levels. In the following the top seven layers of the electricity network are described. The first network level contains power lines at voltages from 380 kV down to 220 kV. The second level transforms the voltage, whilst the third level contains power lines of 150 kV. The fourth network level contains another voltage transformation while the fifth network level contains power lines in the voltage range of 11kV to 22 kV in Zurich. The electricity network model contains approximately 800 nodes on the fifth network level. These nodes represent the electric load of the city in the model used. Transformers are typically installed at the nodes, referred to as network level six. It is worth mentioning that this network level transforms the voltage down to 400 V in the real world. On the 400 V level, power lines, referred to as network level seven, transport the energy to households or other types of loads, which are connected at this network level. While layers one to five are fully modeled, modeling of network level six and seven is limited. Whereas transformers on network level six are modeled in a simplified way, network level seven is modeled only for a couple of selected areas due to data limitations. The latter is investigated in separate work, which is not described here, (see Galus, Art and Andersson, 2012).

The power system analysis tool NEPLAN is used for calculation of the power flow (Busarello, 2008). Its output is exported to Matlab, where the controlled/smart charging is performed in cases where a *flexible demand* is present. Flexible demand means that some vehicles are parked for a longer duration than is required to fully charge their batteries. Hence, these vehicles incorporate flexibility for when they actually have to be charged. This type of load balancing is simulated using a game theoretical, agent-based approach in Matlab. The use of agent-based modeling in TES/MATSim and in the power system simulation ensures the theoretical consistency and integration of both models. More details of this agent-based load balancing are described below.

For management of overloaded resources in the electricity network an approach based on “mechanism design” (Galus, 2012) is chosen. This allows for the optimal allocation of finite resources among competing agents. The competitive behavior of the agents for the resource is based on predefined rules, according to which the agents decide and act. Ideally, this method should lead to the result that those agents who need a resource most are willing to pay the most for it. The willingness to pay can be represented by a utility function (Aumann, 1976). Such allocation of finite resources between competing agents is applied in the case study for electricity load balancing in order to avoid overloaded power lines and transformers in the network, which can result from the additional power demand introduced from electric vehicles. The algorithm allocates power, which can be limited by the physical conditions of the electricity network, optimally among agents. Due to space constraints, the mathematical formulation of this model is not presented here. The mathematical formulation and detailed analysis can be found in Galus (2012) and Galus et al. (2012b).

6.4.5 Scenario Overview

There are four scenarios, which are investigated in this chapter. The parameters of them are shown in Table 6.1. Besides a base scenario of 2010, scenarios A to C are modeled. They represent scenarios with an increasingly higher availability of charging infrastructure and increasing EV market share. Moreover, within each scenario, over time the EV penetration, energy efficiency, availability of charging infrastructure and battery capacity increases. In scenario A, only charging at home is possible. In scenario B charging with higher power is additionally available at work. Furthermore, in scenario B a faster penetration of EVs over time is assumed compared to scenario A (low- vs. high-EV penetration). In scenario C, the charging infrastructure develops at all places faster over time, including public parking spots.

Table 6.1 Scenario definitions of the case study: The three scenarios A, B and C distinguish themselves in terms of market penetration by EVs, charging infrastructure and battery capacity. As various types of EVs are present in each scenario, the driving range is kept constant instead of the battery size. For measuring the driving range the New European Driving Cycle (NEDC) is used (Tzirakis et al., 2006).

			Charging Infrastructure			
Scenario	**Year**	**Market Share EVs**	**Home**	**Work**	**Public**	**Battery**
basic	2010	-	-	-	-	-
A	2020	low	3.5 kW	-	-	80km
	2035					80km
	2050					150km
B	2020	high	3.5KW	11kW	-	80km
	2035					80km
	2050					150km
C	2020	high	3.5KW	3.5KW	3.5KW	80km
	2035		11kW	11kW	11kW	80km
	2050		11kW	11kW	11kW	150km

Although additional experiments with higher battery sizes and charging power have been conducted as part of the case study, those are omitted due to space constraints and can be found in Galus, Georges and Waraich (2012).

6.4.6 TES Integration and Simulations

After describing the different modules and data exchange involved, the present section describes in more detail how this data is integrated into TES for the simulations.

For each scenario run, the vehicle fleet and energy consumption regression models and battery sizes are read in from a file and vehicles are assigned to agents. This assignment of vehicles to agents in the simulation is done in a simplified way: In a preprocessing step, BEV are assigned to those agents with the lowest travel demand. All other vehicle types are assigned randomly to the rest of the vehicle drivers. The assignment of BEV in this fashion is performed to avoid BEV running out of energy during the simulation. As an average weekday is simulated, it is clear that most of those agents, who have electric vehicles, should be able to finish their day without running out of energy in their battery. It is clear that the ownership of different vehicle models is not random in reality, but instead is often based on preferences and attributes of the agents, such as income. This limitation is discussed further in the discussion section.

The setup of the charging infrastructure for the total 13 runs for the case study is facilitated by the options available for defining stationary charging. The stationary charging module allows setting the charging power at each activity location also at once as required in the case study. For charging, the uncontrolled charging scheme is used, meaning that all vehicles start charging immediately upon arrival. In the presented case study, there is no price signal for electrical charging present which might change agent behavior, as this is the case in some of the simulations presented in Waraich et al. (2013a). Therefore, to optimize the run time of the experiments, a MATSim run is performed first with 50 iterations to reach a relaxed demand. This relaxed demand is then utilized as the starting point for the different scenarios simulated with TES, such that only a single iteration is required.

The output of the simulation is then further analyzed with regards to energy and power demand as well as emissions. Furthermore, the electricity demand, SOC and parking times of the vehicles are additionally used as input to the power system simulation, so as to uncover possible electricity network constraint violations. In the following sections the results of the simulations are presented regarding energy demand, emissions and impact on the distribution network. Due to space constraints only a fraction of the overall results are presented here, for demonstration purposes only. The full results can be found in Galus, Georges and Waraich (2012) and Galus (2012).

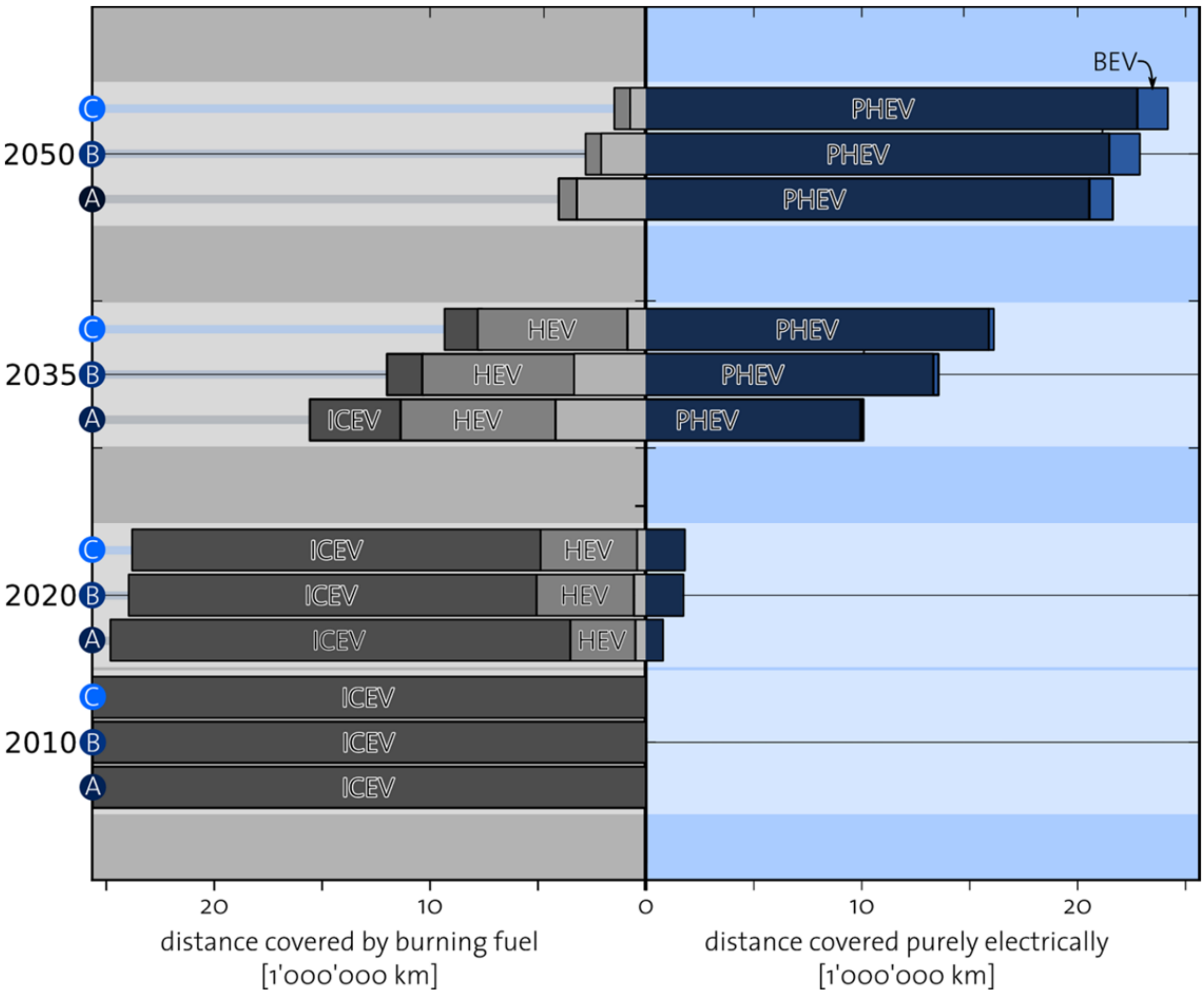
6.4.7 Results – Energy and Emissions

This section looks at the aggregated results related to energy demand and CO_2 emissions for all simulated vehicles, while in the next section the impact on the electricity network for only the city of Zurich is reported.

Although only a 10% sample is simulated, the results refer to the whole population, containing around one million vehicles. As in MATSim a one day period is simulated, the results are meant per day and have not been extrapolated to annual figures. Such an extrapolation would have been quite rough anyway, as only average weekday traffic is modeled and the traffic patterns on weekends are different from those on weekdays. Furthermore, the seasonal effect, including weather conditions would need to be taken into account, which has not been considered. This needs to be explored further, especially as the range of BEV is strongly affected, in a negative way if heating is turned on in winter. Other devices in the vehicles are also not modeled, which would require additional energy to that needed for propulsion of the vehicle.

Figure 6.6, shows the daily travel distance by power train and fuel. Based on the scenario definitions the fleet moves towards more usage of EVs, thus leading to an increased travel distance driven electrically. Scenarios B and C are clearly ahead of scenario A in the year 2035 in terms of usage of electric drive trains, due to the number of electrified vehicles and the charging infrastructure available. This gap is reduced in 2050, as the number of EVs reaches almost the same level as in the other two scenarios.

Figure 6.6 Development of the distance travelled for the whole simulated fleet in scenarios A, B and C for 2010 to 2050, divided by power train and fuel.



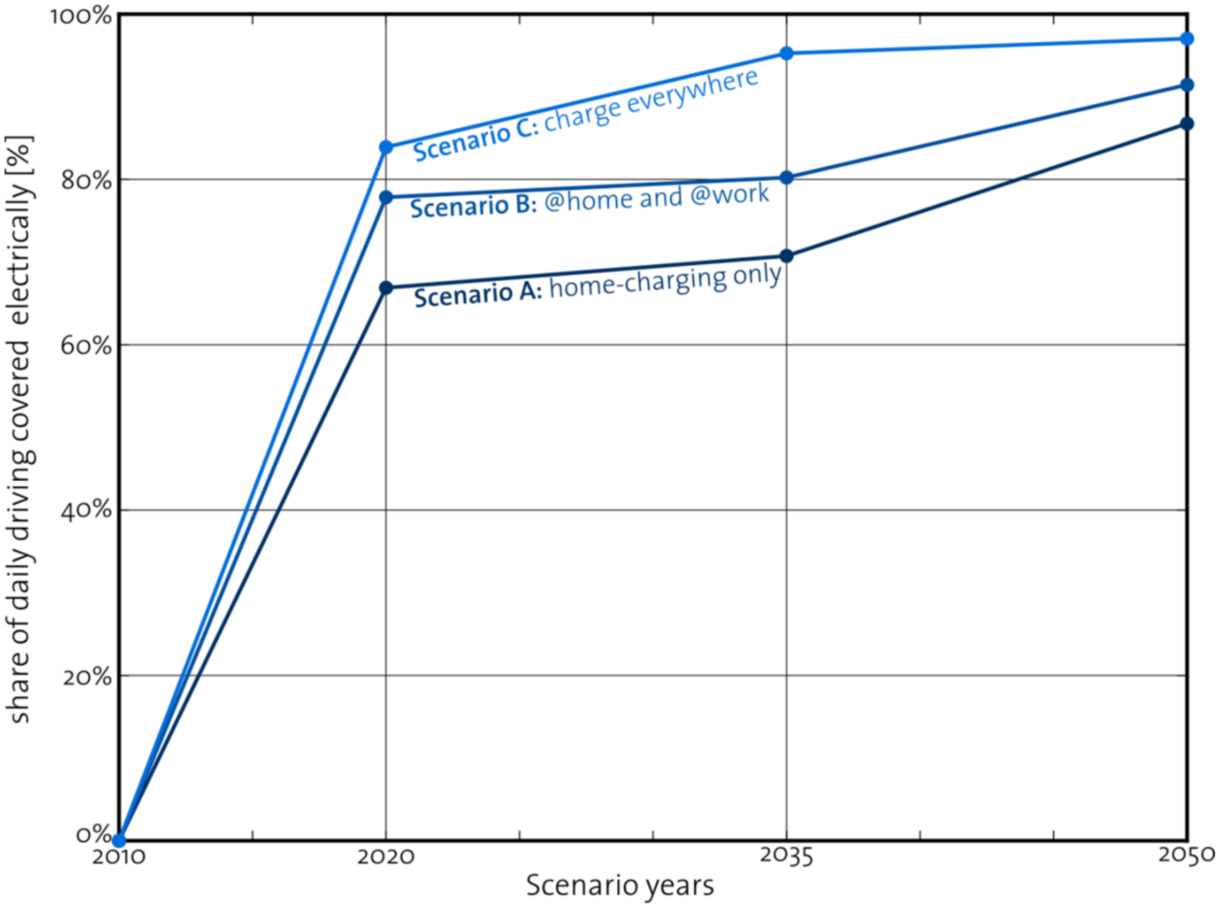
On the left side the distance, which is travelled by using a combustion engine is shown. On the right side the distance travelled using electricity is shown. As PHEV can travel using gasoline and electricity, they are present in the middle in both areas.

In the year 2050, the prevalent powertrain in all scenarios is PHEV. The distance travelled electrically by PHEVs depends on many factors, including:

1. The availability of the charging infrastructure, in terms of number of locations and charging power
2. Battery capacity: the higher the battery size, the longer a vehicle can travel electrically
3. The efficiency of the vehicle – the more efficient the power conversion, the more the vehicle can drive electrically using the same battery size

The influence of availability of charging infrastructure on PHEV electric drive is highlighted in Figure 6.7. It shows for PHEVs the percentage of the distance, which can be performed electrically for the different scenarios. One can see that home charging alone is the most important contributor for allowing PHEVs to drive using electricity and that in 2050 the gap between home charging only and a ubiquitously available charging infrastructure, adds only 10% to electrified driving.

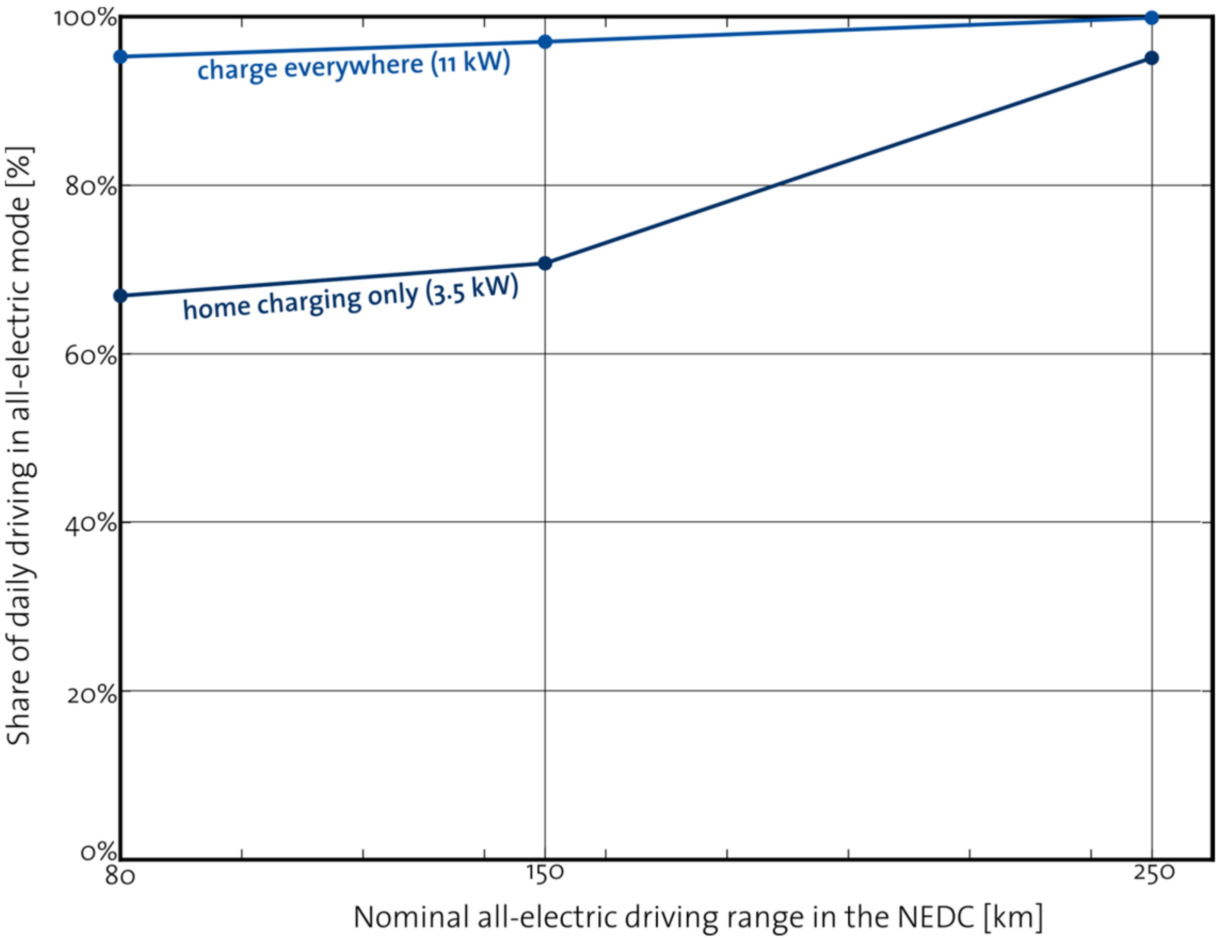
Figure 6.7 Share of the distance travelled by PHEVs, which is driven using electricity for the different scenarios.



Instead of looking at distance travelled electrically by PHEV over time, and charging station availability, one can also look at the influence of battery size in this regard. Figure 6.8 shows the influence of charging infrastructure and battery size on the distance travelled electrically by PHEVs. It uses the results from additional simulation runs, which are not defined in Table 6.1, including battery sizes of more than 250 km. One of the interesting insights of Figure 6.8 is that one can achieve an almost complete electrification (ca. 95%) of PHEV drive in two ways: Either by equipping

PHEV with smaller batteries of 80 km range and at the same time making charging infrastructure ubiquitously available or having large battery capacities of 250 km installed in the PHEVs and making charging only available at home. Furthermore, the figure also shows that if one starts with small batteries (80km range) and only home charging, a 71% electrification of the driving distances is already possible. Both Figure 6.7 and Figure 6.8 provide an overview of the some of the trade-offs involved in closing the gap between this 71% electric drive scenario and a 95/100% electric drive for PHEVs. This can help to design policies, which can best achieve such a goal, e.g. subsidizing home charging, car batteries or investment in public charging infrastructure.

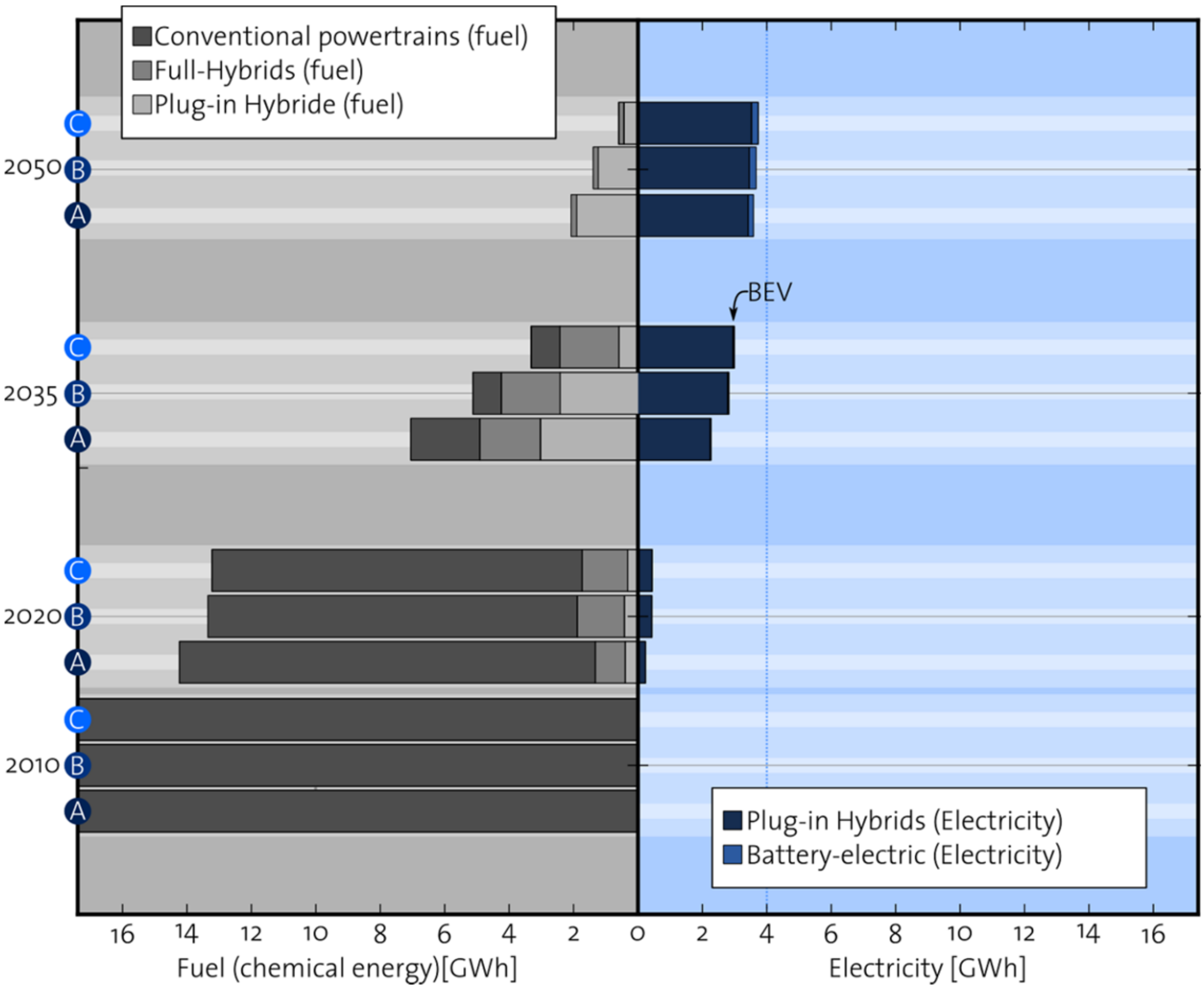
Figure 6.8 Share of PHEV electrical driving distance as a function of the PHEV all electric drive range.



This drive range is measured according to the New European Driving Cycle (NEDC).

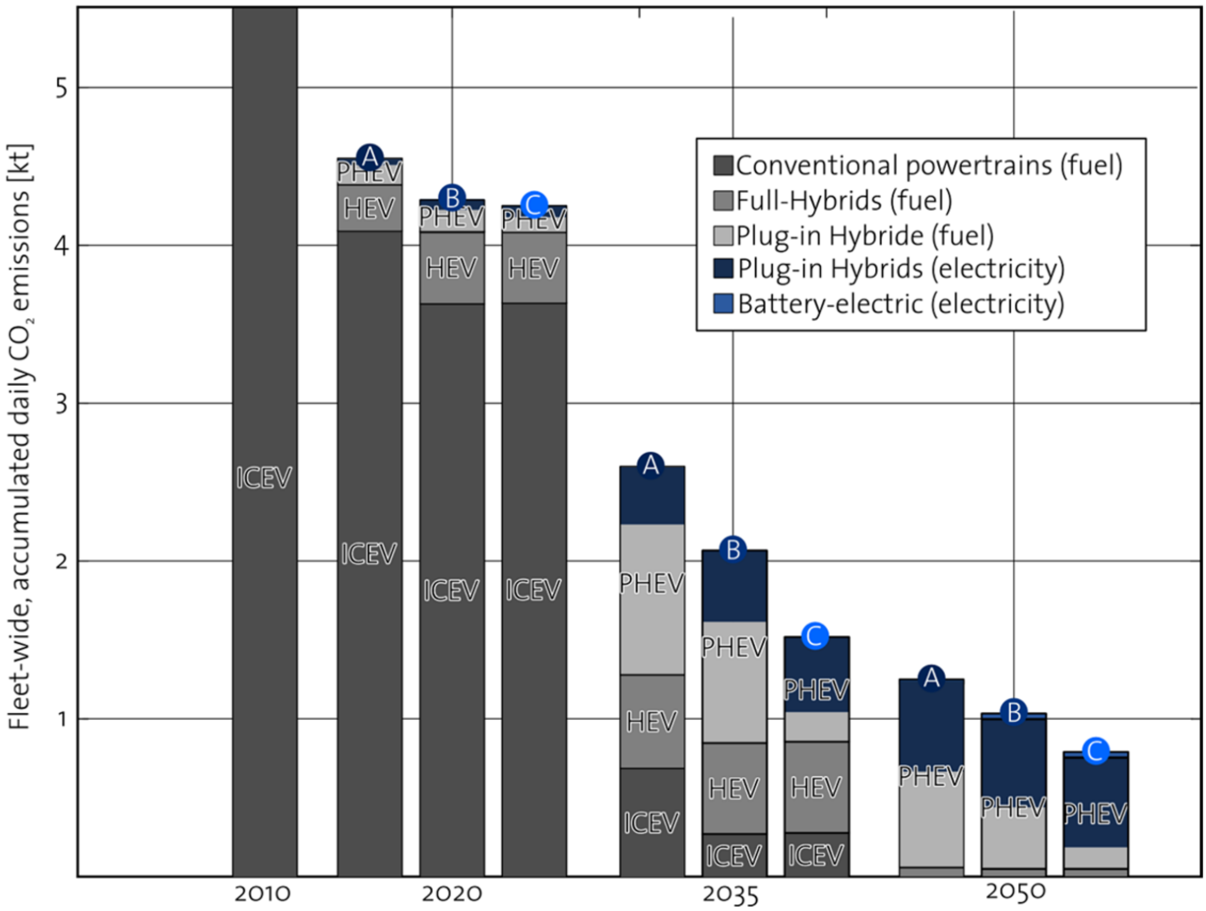
After looking at different influences on the electric drive distance of PHEVs, Figure 6.9 gives an overview of the energy demand of the vehicle fleet between 2010 and 2050 for the three scenarios (A) to (C). The figure shows both the electrical and chemical (gasoline) energy demand. Due to the technological improvement and increasing number of EVs the total energy demand is shrinking and the electricity demand share is growing. While looking at this figure, it is important to remember that gasoline is primary energy and electricity final energy. This means, this figure cannot be utilized to assess the overall reduction of primary energy, as electricity generation depends on the electricity generation process and mix. This means the overall primary energy demand reduction in 2050 compared to base case scenario in 2010 could be far less than the 75% when looking at primary energy and electrical energy combined.

Figure 6.9 The temporal development of the energy demand, by fuel and electricity and according to the different power trains.



The CO_2 emissions reduction is even higher than the reduction in the total energy consumption, which is also attributed to the low emission of the current Swiss electricity generation mix. Figure 6.10 shows the vehicle fleet's daily CO_2 emissions. For the electricity generation, a CO_2 intensity according to the Eco-Invent database is assumed (Frischknecht et al., 2001), taking into account the current energy generation. For the calculation of the emissions 44 g CO_2/MJ_{eq} is used for the Swiss electricity production mix and 88 g CO_2/MJ_{eq} is used for gasoline according to Eco-Invent. In this study neither the import/export, nor the change of the electricity generation mix over time is considered, thus meaning that for all scenarios the current energy mix is assumed.

Figure 6.10 CO_2 Emissions from 2010 to 2050 for the Scenarios (A) to (C) by power train.



The CO_2 intensities of the electricity are based on the average Swiss consumer mix, while the CO_2 intensities of fuel are based on that of gasoline according to the same source (ECO-INVENT, see Frischknecht et al. (2001)).

While the current electricity generation CO_2 intensity in Switzerland is low, especially due to the high share of hydro (54%) and nuclear (41%)

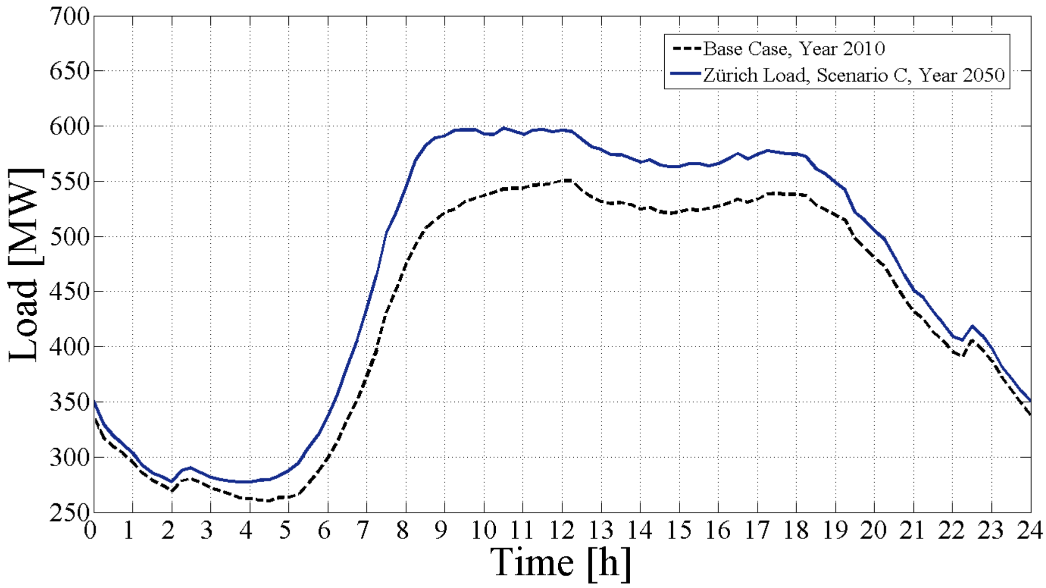
power generation (Bundesamt für Energie, 2011), in the case study it was also considered how the CO_2 emissions could develop if the power generation CO_2 intensity were to become higher. It is found that if most power were to be generated in oil and coal power plans in the future, the CO_2 reductions would probably not be significant enough to justify a shift from conventional to electric vehicles from an environmental perspective.

6.4.8 Results – Distribution Network

In the previous sections the insights of the simulation results with regard to trade-offs between battery size, charging station availability and reduction of energy demand and CO_2 emissions have been discussed. This chapter continues the analysis of the results and looks at the impact of EV charging demand on the electricity network. Although one of the main objectives of the case study presented is to identify congestions, i.e. physical bottlenecks for the energy flow in the electricity network, due to space constraints only one of many investigated scenarios is analyzed. This analysis shows only major results while a detailed analysis can be found in Galus (2012) and Galus, Georges and Waraich (2012). Providing a glimpse into the large number of results, only partial findings for scenario C for year 2050, are presented. Scenario C is most interesting, as it features the highest electricity demand of electric vehicles compared to all other scenarios. In scenario C, people can charge not only at home and work, but also use a public charging infrastructure. Furthermore, the public charging infrastructure allows for faster charging than in most of the other scenarios.

Figure 6.11 shows the aggregated base case electricity load over the day together with the load introduced by EVs in an uncontrolled charging mode for 2050. One can see that the aggregated overall contribution of EVs to the current base load increases the peak electricity demand and also shifts the time of the peak to the early morning hours. The peak demand also changes its shape and becomes more like a plateau at 600 MW, starting at around 09:00 a.m. and lasting until around noon. In the evening hours almost no electricity is charged inside the city. This happens because the charging infrastructure is ubiquitously available. Agents use this infrastructure frequently and charge their vehicles during the day, e.g. at work. Another reason for the low load is that agents living in the city arrive home early between 17:00 and 19:00 and typically do not travel far during the day. Hence, their need for energy to recharge the EVs is small. As only charging inside the city is considered here, most people working in Zurich but living outside the city do not influence the electricity demand in the evening. The peak load increase for 2050 is only around 10% compared to the base case scenario and not dramatic.

Figure 6.11 Aggregated load curves for the city of Zurich for uncontrolled EV charging according to scenario C in comparison with the base case 2010.



While the aggregated peak load increase is relatively small, asset overloads appear throughout the day, between 6 a.m. and 7 p.m., see Figure 6.12. During these hours most of the time at least one transformer at network levels six of the electricity network in the study area is overloaded in the year 2050. The maximum number of simultaneous transformers overloads appears at 8.30 am, when 10 transformers are overloaded at the same time. Such asset strain appears low for a scenario which deals with a load in the year 2050. However, in order to accommodate a maximum of the EV load while considering an as yet uncertain network development in the future, it is assumed that the installed transformers at network level six could be loaded to their full installed capacity rating. This is normally not the case for redundancy reasons which help ensuring security of supply.

Figure 6.12 Number of overloaded transformers on the 11 kV and 22 kV level of the electricity network.

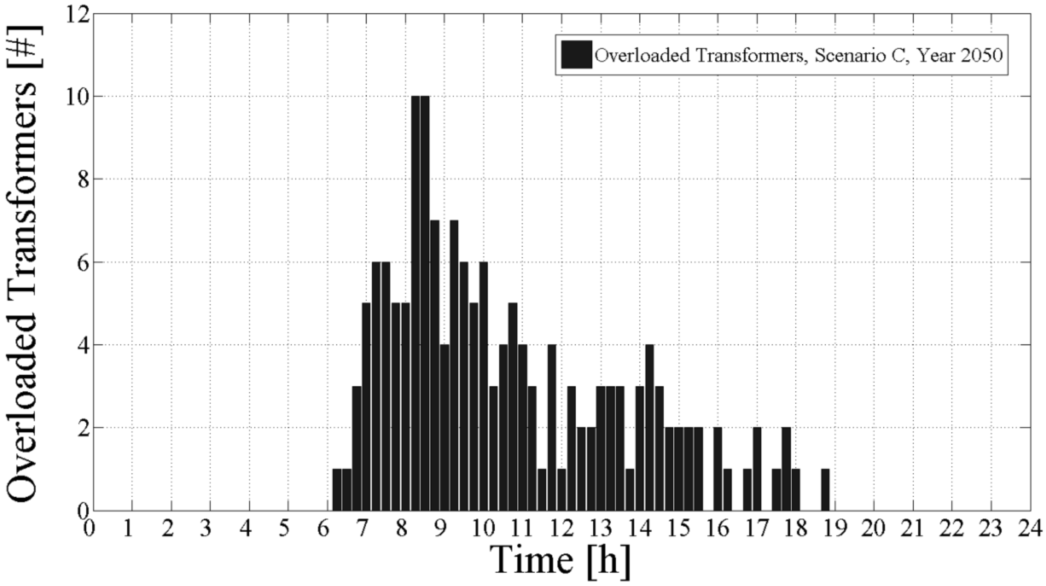


Figure 6.13 Development of the EV electricity demand in Scenario C in 2050 at all nodes of the 11 kV / 22 kV electricity network.

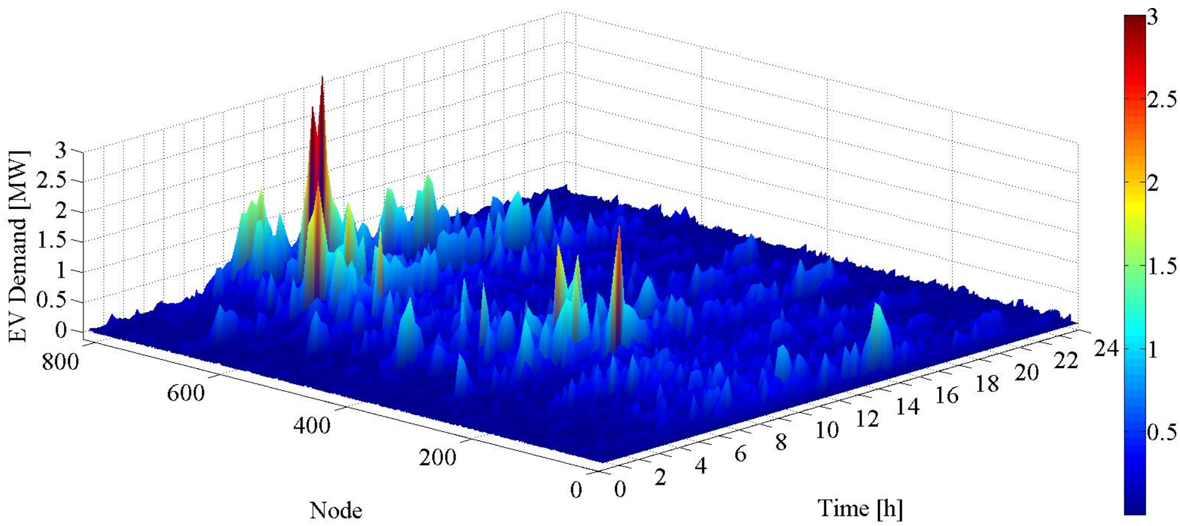
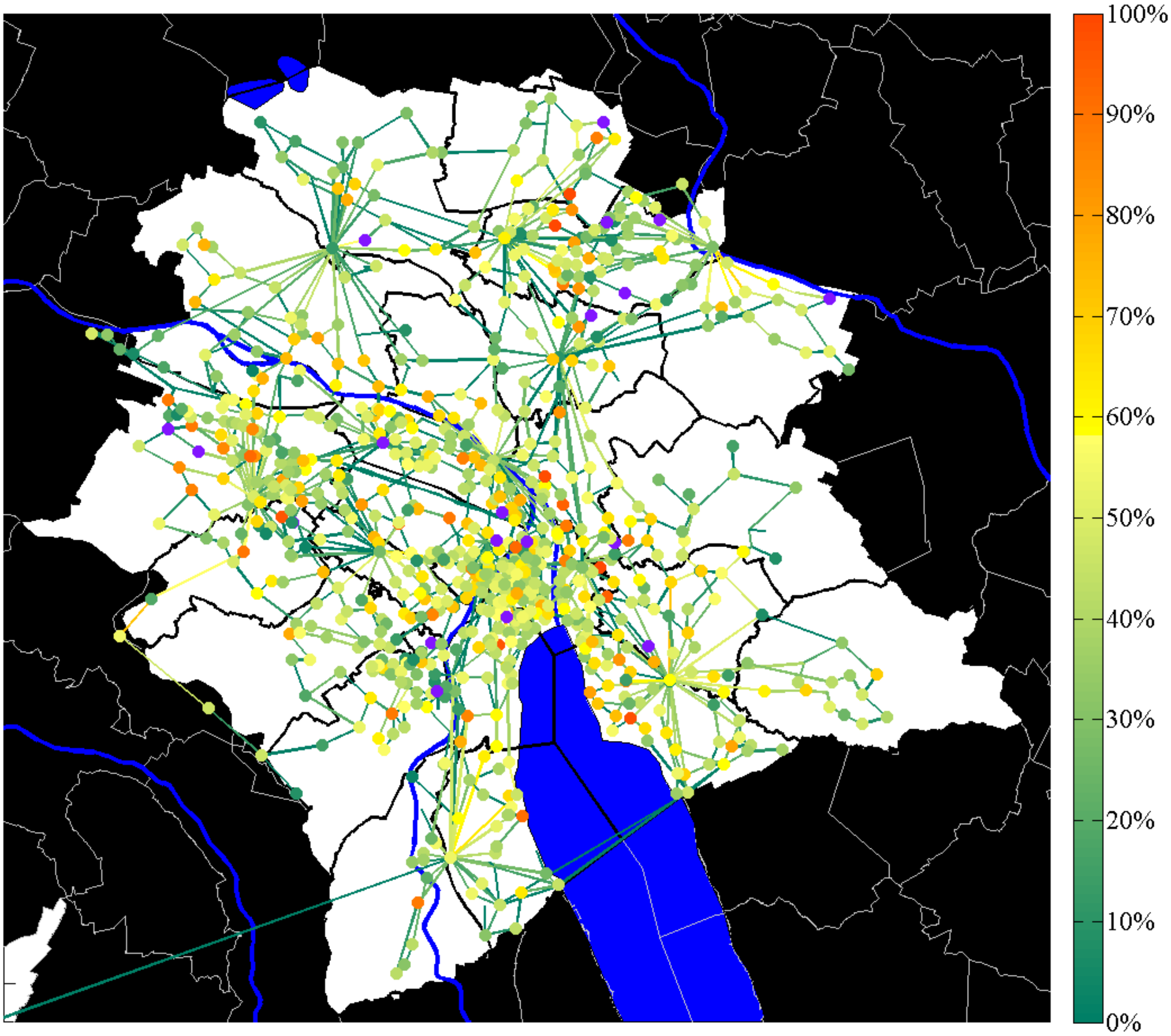


Figure 6.13 shows the EV load at all nodes of the electricity network on the 11 / 22 kV voltage level. The situation is quite serious, as at certain nodes peaks of almost 3 MW occur. This happens due to the high charging powers which are available in this scenario. Although vehicles arrive with a relatively high SOC, when connecting to the network they often show a quite high degree in the simultaneity of connection. Their load adds up, re-

sulting in the few, but high peaks. However these peaks do not last long, as the EVs in this scenario usually arrive with a high SOC as they are relatively efficient. In this study the EVs consume on average 130 Wh/km while other studies use an average consumption of 500 Wh/km, (see e.g. Galus 2012).

Figure 6.14 A snapshot of the spatial distribution of electricity network resources and their utilization at 10 a.m. for the 11kV network of the city of Zurich.

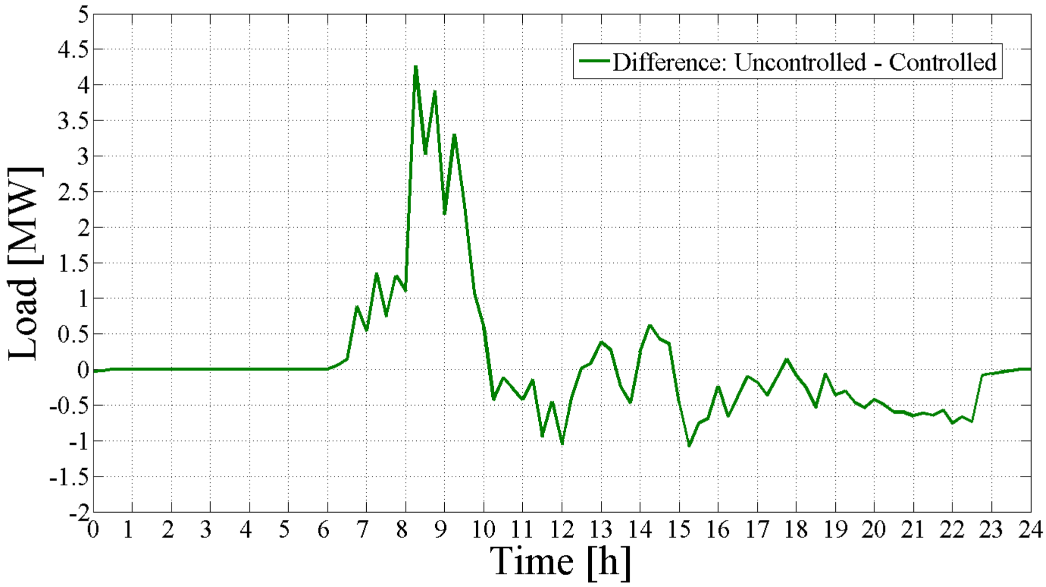


The dots denote transformers, while the links denote power lines. The resource utilization is color coded from green (0%) to red (100%), while violet indicates an overloaded resource.

While many transformer overloads occur in this scenario, power line constraint violations are not severe. Only one power line reached a level above

60% of its rated power. A temporal and spatial visualization of the load situation of the distribution network in scenario C for the year 2050 can be prepared. A snapshot at 10 a.m. of the load situation is shown in Figure 6.14. Violet dots and links represent network assets (transformers and power lines), which are overloaded.

Figure 6.15 Shift of load due to controlled charging in Scenario C in the year 2050.



Positive values indicate, that the uncontrolled EV load is bigger than the controlled load.

In order to try avoiding the transformer overloads, controlled charging is performed using the load balancer. Through controlled charging, the peak load resulting from EV charging is reduced. This is achieved by charging vehicles at later times if possible. Figure 6.15 shows the difference of load imposed on the electricity network of the controlled and uncontrolled charging scenario. A positive value indicates that the load in the uncontrolled charging scenario is larger than in the controlled charging case. Obviously, the load in the morning hours is reduced and shifted into evening hours by using the load balancer. However, after following the controlled charging strategy there appears a difference in the total energy charged in uncontrolled and controlled manner. The difference is not negligible and can be quantified to 2.4 MWh. This means, some EVs leave their parking lots with a SOC that is lower than their desired SOC for departure. This is due to heavily congested nodes, which do not allow, even when utilizing the complete temporal charging flexibility, to fully charge some EVs. A solution to this is to expand the network infrastructure selectively where bottlenecks arise, i.e. building more power lines and transformers. Another solution could also be to provide feedback to the vehicles which include information on temporal and special congestion in the network, e.g. through varying prices charged for electricity. This would allow vehicles to react and adapt their temporal and special charging patterns. This approach has been demonstrated successfully by Waraich et al. (2009b) and Galus et al. (2012b).

6.5 Discussion

In the following, a couple of issues, especially in relation to the TES framework are discussed together with future work, following which the discussion will be directed more towards the framework itself.

6.5.1 Case Study Discussion and Future Work

In the case study, several simplifications are made, of which one of the most fundamental is in relation to future scenarios, where neither the population nor road network or distribution network are updated to fit a possible future scenario. An attempt is made to improve this aspect of the MATSim scenario within a different project for Switzerland, where planned road projects and federal projections of Swiss population growth are taken into account in the simulations, (see THELMA, 2013).

A second simplification, which has been previously alluded to, is that an average working day is simulated, omitting simulations of Saturdays and Sundays, which exhibit different traffic patterns. Furthermore, seasonal changes also have impact on the energy consumption (cooling and heating), which would also need to be considered for calculating annual figures. In this regard there is clearly potential for improvement, which some of the authors hope to tackle further in THELMA (2013).

Two experimental design issues are highlighted here, regarding the number of runs conducted. It is common knowledge that a single simulation run counts as a single experiment and that one needs to perform several experiments in order to be able to report variance of simulation results. Unfortunately, this was not possible due to time constraints for the case study at hand. In order to still give a sense of the order of magnitude of variance encountered between runs, variance from previous experiments are reported here. Horni et al. (2011a) reported on the variability of different

MATSim runs in the region of Zurich employing a 10% population sample. The variability at street count stations for the whole day is mostly in the range of 1 to 7%, with a mean of around 4%. This variation between the runs is higher on average when looking at specific hours, with most of them in the range of 10 to 15%. The variation expected for the runs conducted in this case study is lower, as the destination choice module used during replanning is not utilized, which is the case in Horni et al. (2011a). Furthermore, Horni et al. (2011a) applied a higher replanning rate of agents per iteration than that used in this or earlier studies, in order to accelerate the convergence of destination choice (20% replanning vs. 10% replanning used in this chapter). Population sampling is certainly also an additional factor contributing to increased variability of traffic volume counts, thus meaning that the variance figures reported would probably drop if population sample bigger than 10% were used.

An additional reason why repetition of the experimental runs would be required is that vehicles are assigned to people in a random fashion. While it is verified that this had only little effect on aggregate results, no such analysis was possible for the results regarding the electricity network. However, one can argue in this regard that the omission of such repeated runs does not have a significant impact on the current results: A large variance would be expected for such areas where only a small number of cars are present, such that a switch between non-EV and EV would have a big impact. However, such areas are of less importance to the electricity network results, because bottlenecks normally arise in high demand areas. In these areas the variance of demand between runs should automatically drop due to the larger number of vehicles involved.

The random assignment of vehicles to people is also not appropriate, but instead a model like that by Jäggi and Axhausen (2011), could be used to define which household is more likely to buy a certain type of car. Furthermore, neighborhood effects could also be modeled for adoption of new vehicle types, as investigated by (Axen et al., 2009) through stated and revealed choice experiments.

The assignment of BEVs to people is achieved by assigning them to those people, travelling the shortest distance over the day. There are enough such candidates, as the average daily driving range in the study area is far less than the 80km minimum battery size available to EVs (Bundesamt für Statistik, 2013). In addition to person attributes, an improved model could also take the driving range of the vehicle into account, as part of the optimization in the simulation. A similar approach has been adapted in the simulation of Knapen et al. (2012).

In comparison with the authors' previous work (Waraich et al., 2009b), in this case study the TES framework is only used for demand modeling. Controlled charging is achieved through use of the external load balancer modules. Furthermore, the data flow in this case study is only one way from TES to the power system simulation, while an iterative interaction between TES and the power system simulation is presented in Waraich et al. (2009b). As there are no prices for electricity/special EV parking involved in this case study, agents did not exhibit any change in behavior due to EV ownership, as has been successfully demonstrated within similar context in the past. See e.g. Waraich et al. (2009b) or Waraich and Axhausen (2012b).

As mentioned in the background section, it is pointed out by Binding and Sundstroem (2011) that the degree of integration of their models is higher than present in our approach. While such tight coupling has advantages in term of performance, there is also a downside to it: For such full integration all program code needs to be developed within the same programming language which is often not possible, as the programming languages and libraries used in the different expert fields vary. By integrating loosely coupled models written by different domain experts, within the the presented case study far more advanced models could be integrated than is the case in Binding and Sundstroem (2011), e.g. for demand side modeling.

6.5.2 Framework Discussion

After discussing the TES framework within the context of the case study, in this section a more general discussion of the TES framework is presented.

As the target audience of the framework two major groups of users can be envisioned: Firstly interdisciplinary teams, who would like to perform case studies related to electric mobility for a specific study area. To such people the TES framework does not only provide the benefit that models developed by other researchers can be reused, but TES also provides a common platform of thinking, about how the problem at hand can be addressed, while facilitating interoperability of models.

The second target group of TES users are those who do not work within an interdisciplinary team, but would still like that their models are used beyond simple test scenarios or in case studies with narrow scope. To such users TES provides a platform, where models from various fields of expertise can be reused. This facilitates the implementation and integration of new models by such users. Furthermore, TES makes it easier for such users, that their models can be adopted by a wider audience within the research community than before.

A question which might arise in this regard is, why should people change their behavior and start providing their models for reuse to others for free, although this was not the case till now? There are several points which need to be discussed. At the moment most research is presented either in written form through scientific journals or via presentations at conferences. A platform, where research related to electric mobility can be reused, is an ideal place to advertise new related work. This could increase the reuse, visibility and impact of the work within the overall research field, which is probably one of goals of most scientific efforts. Furthermore, by having a platform with standardized interfaces, it becomes simpler to compare different models and to get feedback from other users regarding it. Also providing good documentation to modules is as such in the self-interest of the module creator, as this increases the chance that the module gets used and can improve through feedback.

While it is argued above that it should be in the self-interest of module creators to provide their modules for free, in the following it is discussed whether or not such modules must always be open source. While it is advantageous to provide a module open source in order to get detailed feedback, in some cases, people might want to provide their work to others for reuse, but not allow them to see the detailed implementation. The reason behind this might be to advertise the work to others for reuse, while still wanting to maintain a competitive research advantage. For example, one might have an extension of a module or its publication planned and one may wish to protect against other researchers doing the same extension quicker. A second reason for not providing the source code might be that one does not feel comfortable with showing the details of the source code. For both situations, instead of contributing the module source code, compiled modules can be contributed to TES instead.

Another question relates to how such a framework can be maintained over time. There is a range of possibilities when it comes to how the framework might be supported. In the minimal case, just the framework is made available to others for use and one needs to provide a way in which, people can contribute new modules and search existing ones. This could be done either by hosting those modules with documentation at the framework's website or by providing an external link to such resources.

However in order to promote the framework, one would probably need to do more than the bare minimum described above, possibly including advertising the framework to potential users and contributors whilst also providing them with help through tutorials and possible collaboration. In order to maintain the quality of new modules contributed, one might also need to provide and enforce guidelines, e.g. minimum standards regarding documentation and testing. It might also be necessary from time to time to keep the framework up to date with the most current version of MATSim. Whilst it is tried to base the implementation of TES only on parts of MATSim, which are deemed stable, such as event handlers, there might be parts which could require an update to a newer version at the request of users. For example, if users may require more advanced features of MATSim, which are not available in the current MATSim version compatible with TES.

6.6 Future Work

Although some of the future work has already been mentioned previously, in this section work in progress and planned work for TES is described further.

It is planned to make the framework available until the end of 2013, at the URL www.tesfw.org (Transportation Energy Simulation FrameWork). This will require preparation of documentation and examples. In the longer run, it is also planned to work towards animated visualization of EVs and the provision of tools for simpler use, as mentioned earlier. Furthermore, modules which are still work in progress are also planned to be part of the framework when it is published, including optimal placement of charging stations and a module, to allow for simple extension of vehicle types to support a solar panel roof and a module for modeling the spatial and temporal intensity of the sun shine (Perez et al., 1990; Gadsden et al., 2003). Also regenerative braking, which is often present in EVs has not been modeled till now and needs to be taken up in future.

With regards to the usage of charging stations, such as fast charging and swapping stations, there are at least two strands of modeling which seem possible. The first approach is a simpler and higher performance solution, which does not adapt agent plans for rerouting to charging stations during the simulation, but changes plans only at the end of the simulation whilst keeping track of utilization constraints of charging stations and taking agent decisions into account. A second approach could adapt the plans during the execution of the micro-simulation, which would be more accurate. The downside of this approach is, that it is more complex than the first approach and tightly coupled with the MATSim micro-simulation implementation and is therefore slower than the first approach. Therefore it is more likely that the first approach will be included in the framework first.

Something, which has been entirely ignored within the TES framework until now is the energy demand of buildings and especially of homes. This seems to be especially important, as the electric vehicle is part of the energy system at home, which includes electricity generation, e.g. from the solar roof of the home/vehicle, demand response to shed load at times of overload in the electricity network, including those of home appliances (Farhangi, 2010; Robinson, 2011) and V2G. Indeed, more research in this direction is essential in order to ascertain what kind of interfaces should be provided for such modeling of these scenarios as part of the TES framework.

As mentioned previously, the assignment of vehicles can be either modeled externally or can be a part of the simulation. This would require the implementation of replanning modules, which do not only consider choice between travel modes, but also between vehicle types, especially BEV and PHEV, where travel distance and preferences of agents are taken into account, similar to the approach taken by Knapen et al. (2012).

Other things, which must also be evaluated include how electricity supply and generation modules can be best made available in TES or if this needs to be solved externally and what interfaces would be required for that. As many modules require optimization libraries for such implementation, this work needs to be facilitated by providing examples of how to use such optimization libraries in TES using Java.

6.7 Conclusions

In the introduction several open questions related to the electrification of driving are posed which focus on the notion that while many studies have tried to solve such problems, there is a lack of work looking into detailed and combined demand and supply side modeling. It is argued in this chapter, that such a development is present due to the lack of an environment allowing reuse of models, developed by other researchers.

In order to propose a solution to this problem, an open source framework is presented, which could bridge this gap. This is achieved by generalizing previous work beyond single case studies in the form of a framework, which will be published online. Furthermore the framework is open for extension and reuse. In this way, the framework provides a common ground for interdisciplinary work and contribution, it is hoped that the overall research of electric mobility will benefit from it.

In this chapter, also an application of the framework is presented, which looks at the impact of EV charging on the electricity network of the city of Zurich, together with environmental analysis. To the best of our knowledge, this is the first study of its kind in terms of detailed modeling and size. Using simulation experiments possible bottlenecks in the electricity network are uncovered. Furthermore, different options and trade-offs are outlined. These results can be used by the utility provider in the city of Zurich for their planning of the electricity network. Furthermore policy makers can design incentives, while taking such additional input into account.

In the complex realm of challenges and opportunities, which are present through the introduction of EVs, the presented framework can help all stakeholders involved in planning for a more sustainable future.

Chapter 7

Conclusions and Future Work

7.1 Results and Conclusions

This dissertation has contributed to state-of-the-art integrated electric vehicle modeling. While the focus is on electricity demand modeling, integration with electricity network flow and supply models has also been successfully demonstrated for large scale scenarios. As the simulations in Chapter 6 demonstrated, the developed demand models can be used in combination with supply models to pinpoint possible bottlenecks in existing electricity networks that could arise in future. This can help electricity network planers to prepare the current electricity network for possible large scale EV charging. This experiment also demonstrated that the developed models are unique in terms of the methodology used, the scenario size and their temporal and spatial resolution.

As argued in Chapter 6, in order to promote interdisciplinary work related to electric vehicles, a publically available common framework is needed. This dissertation attempts to fill this need by making its work publically available. Although the intention is to make the work available by the end of 2013, several researchers from various research institutes have shown interest in contributing their models to the framework.

This dissertation has also contributed to agent-based travel demand modeling through a new traffic micro-simulation model geared towards high performance simulation. Additionally, various parking models have been developed within this dissertation and their application, especially in the area of policy design, has been demonstrated. However, in this dissertation just a small set of applications of the various developed models have been demonstrated. Particularly when considering the wider scope of the framework (see Chapter 6 introduction), it seems that this dissertation only demonstrates a glimpse into the possible uses and extensions of the framework. Possible future work is described in the next section.

7.2 Future Work

All chapters of the dissertation contain their own section of future work. Here only a few high level future work ideas are summarized, including new ideas.

7.2.1 Performance

The performance improvements to the MATSim simulation presented in Chapter 2 were conducted in the year 2009. In the meantime, several additional performance efforts have been conducted, such as an effort to parallelize JQueueSim (Dobler and Axhausen, 2011). However, JDEQSim is still faster in most cases using a single CPU (Dobler, 2013).

As many applications including parking search and electric vehicle speed charging require change to the original route of the vehicle during the simulation, these types of simulations create additional computation burden to for the MATSim simulation framework (this feature is sometimes referred to as "within-day replanning"). One possible solution in this situation could be to perform less detailed simulations based on travel time calculations from previous MATSim iterations, as suggested by Fourie et al. (forthcoming 2013). Therefore, besides the ideas provided in Chapter 2 for performance improvement, an event-based model using travel-time matrices from previous iterations combined with "within-day replanning" could also help to accelerate the simulation further. The author has worked on initial experiments in this regard, which are promising.

7.2.2 Extension towards Several Parking Search Strategies

Chapter 5 uses an initial implementation of parking search, however as a parking strategy is adopted which reserves parking ahead of arrival using a mobile phone, no parking search related traffic is present. Future work could build on a recent conceptual paper presented by the author at an international conference on travel behavior research (Waraich et al., 2012), where it is proposed that instead of having a single parking search strategy as often adopted (Benenson et al., 2008), multiple strategies should be considered. The idea is based on the observation that in reality people looking for parking often cannot chose at the starting of the parking search process where they want to park, but instead they just chose a parking search strategy for how to look for a parking (see, Axhausen and Polak, 1989). This means people have several possible strategies at their disposal and one is chosen which based on experience could render a good utility, in terms of walk distance, parking cost and search time. Implementation and application of this for Zurich is planned for the near future.

7.2.3 Application of Smart Charging to a Real World Scenario

In Chapter 3 an iterative approach between demand and supply systems is presented where demand generation is followed by the discovery of bottlenecks in the grid, which is fed back into the demand generation process. Due to the computation time and complexity of such modeling, this has only been demonstrated on a toy scenario. However, the intention is to enhance the work presented in Chapter 6 such that this can be applied to the presented Zurich scenario.

7.2.4 Technology Relationships: Complementary or in Competition?

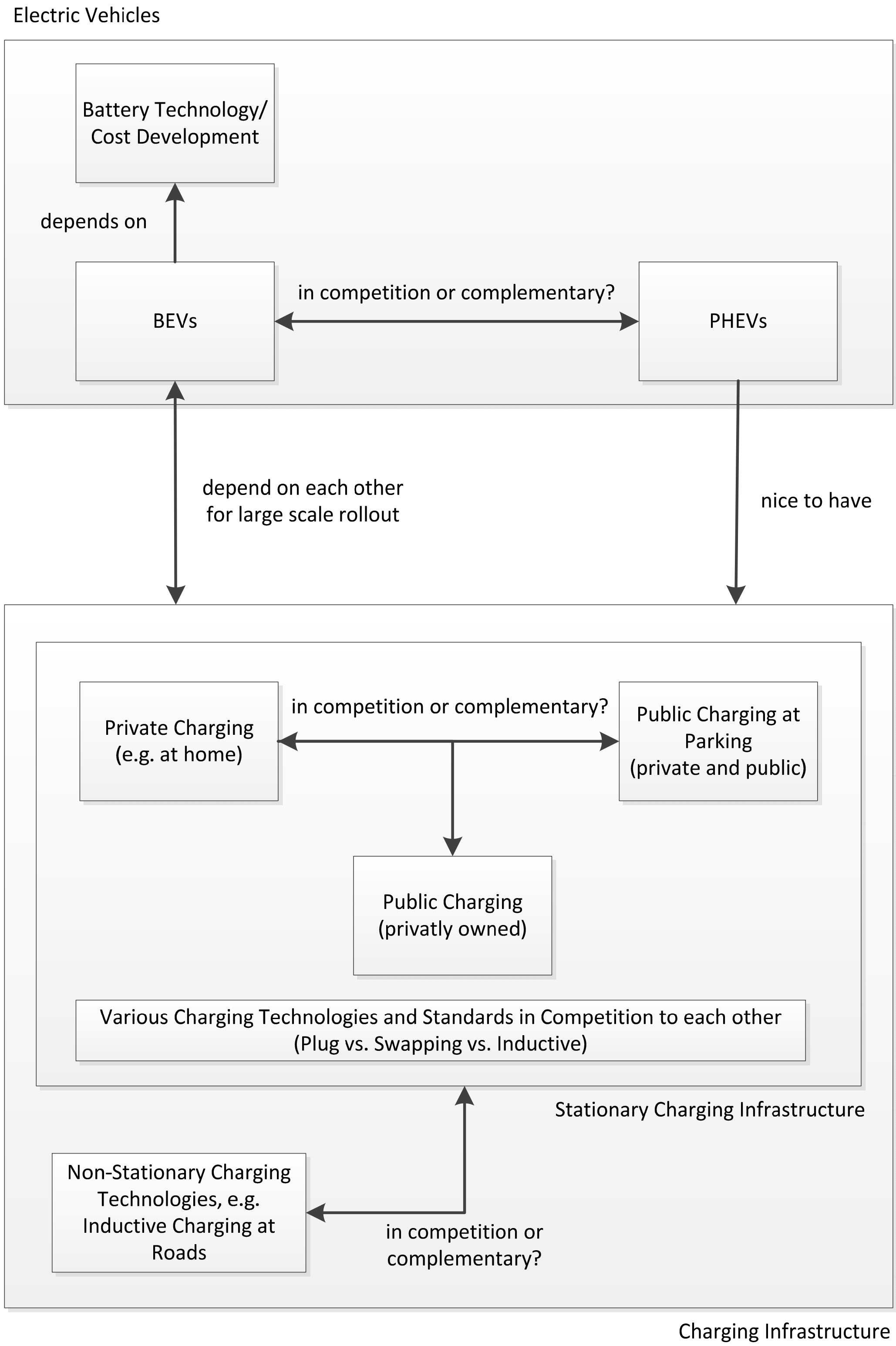
In this dissertation, PHEVs and BEVs have been summarized as EVs in most places and charging infrastructure is presented in a quite abstract way. However, this picture hides several technological competitive relationships among vehicle technology and charging infrastructure. A sketch of these relationships can be found in Figure 7.1.

Without going into detail about the complex relationships involved, the major questions is: will a large scale public charging infrastructure be built and will it be profitable? From the perspective of private firms, investing in public charging could be seen as a high-risk investment. The usage of such infrastructure depends on the development of battery technology; if large batteries become affordable, the demand for public charging will fall. Furthermore, such public charging infrastructure is in direct competition with private home/work location charging infrastructure, where the latter has a clear advantage in terms of location and price. There is also an ongoing competition between charging technologies and their standardization, which hampers private investment in public charging infrastructure even further.

This situation slows down the adaptation of BEVs, which have a disadvantage compared to PHEVs due to anxiety about their range and in terms of cost, as long as batteries prices make up a major part of the cost of these vehicles. This general chicken and egg situation can however change drastically when the boundary conditions of the problem change, for example due to government subsidies, bias in user preferences in favor of zero emission technologies or investment of firms with long term goals.

Within this context the models developed so far could be extended to simulate investment decisions by individuals, private investors and the government. Such a model could include decisions about vehicles (BEVs vs. PHEVs) and investment in charging infrastructure by individuals, and investment in infrastructure by private investors and the government. Furthermore, the model could be developed in such a way that it is responsive to government subsidies, e.g. in vehicle cost and private and public charging infrastructure. It is clear that such simulations can become quite computationally intensive, therefore simpler traffic simulation models could be used as mentioned earlier.

Figure 7.1 Technology relationships: complementary and/or in competition?



7.2.5 Future of the Framework

Several models of the TESF framework are in development or their development is planned in the future as outlined in Chapter 6. A couple of researchers from Europe, USA and Asia have shown interest in the framework and are contributing to it with new models. It is expected that with the official publication of the framework by end of this year model contributions to the framework will increase, which is in accordance with the goals of the framework.

Currently, the framework focuses on the electricity demand of electric vehicles. A natural next step in the development of the framework is to extend the model to incorporate the heat and energy demand of buildings. Ideas for post-processing the output of MATSim for modeling the energy demand of buildings exist and could be integrated into TESF (Robinson et al., 2009). Other applications of the framework where the framework is extended can also be envisioned, such that it also includes additional resource demands and their flows, for example those of food and water and waste generation in a city (Sivakumar et al., 2012). Several other extensions and applications of the framework can also be imagined, especially with regards to policy design as demonstrated throughout the dissertation.

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